Increasing importance and new behaviors, a new era for retail investors, how does their performance measure up?

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Abstract

This study examines the performance of the Robinhood (RH) consensus portfolio from 2018 to 2020. It refutes Welch's (2022) analysis that the consensus RH portfolios performed well, by showing its last months' influence on alpha's abnormal return. This study reveals that while RH investors leaned towards trading volumes higher than the 12-month average, this alone does not explain their abnormal returns. I argue that the portfolio performance is mostly explained by the onset of the Covid-19. I defend that RH users largely benefited from increasing engagement during this period, intensifying holdings following major market shifts, notably during the 33% drop of March 2020. I conjecture that this, along with investing in stocks that see high absolute returns positively, contributed to the portfolio performance post-2020.

Keywords: retail investor, crowd portfolio, linear regression, market participation, investors behavior, trading, Covid-19 pandemic.

Título: Importância crescente e novos comportamentos, uma nova era para os investidores singulares, como se mede o seu desempenho?

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Abstrato

Este estudo examina o desempenho do portfólio consensual da Robinhood (RH) de 2018 a 2020. Refuta a análise de Welch (2022), que afirma que os portfólios consensuais da RH tiveram um bom desempenho, ao mostrar a influência dos últimos meses no retorno anormal do alfa. Este estudo revela que, embora os investidores da RH se tenham canalizado para volumes de negociação superiores à média de 12 meses, isso, por si só, não explica os seus retornos anormais. Sugiro que o desempenho do portfólio é principalmente explicado pelo início da crise da Covid-19. Proponho que os utilizadores da RH beneficiaram largamente do aumento do envolvimento durante este período, intensificando as suas posições após grandes mudanças no mercado, nomeadamente durante a queda de 33% em março de 2020. Defendo que este efeito, juntamente com o investimento em ações que registaram elevados retornos absolutos, contribuiu positivamente para o desempenho do portfólio após 2020.

Palavras-chave: investidor singular, portfólio de multidão, regressão linear, participação no mercado, comportamento dos investidores, negociação, pandemia de Covid-19.

Content

Introduction

Retail investor’s participation in the financial markets has drastically changed over the past decades. Trading costs have generally followed a decreasing trend since 1990 (Adams et al., 2023). 2019 is a tipping point where online brokers collectively moved towards commission-free trading.

Robinhood for instance, provides an environment with little complex financial information. It attracts a new form of retail investors with half of Robinhood users being first-time investors in 2020 (Robinhood, 2020). This new wave of less financially educated retail investors is more likely to be influenced by attention (Seasholes & Wu, 2007).

The reduction in trading costs and the financial innovations introduced by FinTechs have contributed to reshaping the profile of an average retail investor. They also now take a much larger share of markets’ order flow. In 2020, the share of retail investors in US equities reached 20% of the total trading volume. This is double the trading volume of retail investors a decade before (McCabe, 2021). They now have a newly established impact on markets, particularly on small and medium capitalization (Barber et al., 2022).

To summarize, these factors support the notion that retail investors have changed, leaving a unique impact on financial markets due to shifts in their size and behavioral tendencies.

Despite the contrasting views in existing research concerning retail investors' performance, recent swathes of retail investors bring unique attributes that may necessitate a reevaluation of their behavior in financial markets. This is the subject of my thesis: Increasing importance and new behaviors, a new era for retail investors, how does their performance measure up?

In this paper, I will investigate investor’s investment decisions at the aggregate level. The analysis will be based on recent research from Welch (2022) and Fedyk (2023) assessing retail investors from a crowd perspective.

I will leverage a publicly available dataset from Robinhood (RH) covering the period from May 2018 to August 2020. Over this period Robinhood made available an API that could query the amount of users investing in each security available with this broker.

This means that I will look at RH users collectively and asses their portfolio-level holdings with weights defined as the number of investors holding that security divided by the sum of all investor counts for all security in the investment universe available to RH users. Such portfolio can be perceived as a « consensus statistic» or «crowd wisdom» portfolio (Welch, 2022). The core of my analysis will be focused on Public US Equities but the dataset includes other RH holdings.

I find that over the sample from June 1st 2018 to August 14th 2020 RH investors performed particularly well. The Aggregate RobinHood (ARH) portfolio did not underperform. Alphas from Fama and French's five factors and momentum model, 6 factors from here onwards, are significant with daily and monthly rebalancing. I observe a statistically significant 7.19 basis point daily Alpha with a daily rebalancing and a 1.23% monthly Alpha with monthly rebalancing. Particularly, the latter shows no look-ahead bias, is easy to implement, and corresponds to an annually compounded 15.80% alpha.

These results are consistent with Welch (2022) and Fedyk (2023) findings. Building on the former's research, I test for a proxy portfolio that Welch (2022) defines as QRH, based on volume metric. While returns exhibit an astonishing 96.84% correlation with the ARH portfolio returns this only explains 18% of ARH investors' Alpha. A still statistically significant 1% Alpha seems to suggest that skills may explain investors' overperformance above trading on volume signals.

Expanding beyond the scope of existing research conducted by Welch (2022), I have discovered that the sample period, which overlaps with the initial market collapse and lockdown regulations due to Covid-19, is key in understanding ARH portfolio performance. This finding presents a challenge to previous conclusions, suggesting that the unique circumstances of this period may have significantly influenced investor performance. Indeed, I show that ARH's overperformance is nonexistent before 2020. The significant alpha over all periods is only explained by large overperformance during the 6 months of the sample in 2020. The later shows a significant 18.5 basis points Alpha, significant at the 1% level with only 156 daily observations. I argue that conditions peculiar to this period, stay-at-home orders and increased free-time availability, stimulus checks, and RH users' market contrarianism during 2020 and both the market collapse and recovery explain this result. Finally, I argue that RH users may have benefited during this period from investing in stocks that see large abnormal absolute value returns. Fedyk (2023) defends that they may have benefited under some circumstances from Buy The Dip (BTD) effect, particularly when investing in large capitalization. Barber et al. (2022), claim that this pattern leads them to consistently exhibit negative alphas on these trades.

This paper proceeds as follows. Section 1 is this introduction. Section 2 delves into the background of my analysis and literature review. Section 3 discusses the data and methodology I use. Section 4 analyzes ARH crowd portfolio performance and its proxy. Section 5 discuss the impact of the covid pandemic and the overall portfolio performance. Finally, section 6 concludes.

1 Literature review

I made the point that retail investors' participation in financial markets had been largely disrupted by fintech's innovation and a collective move toward commission-free trading (Adams et al., 2023).

These types of platforms get revenue from a Payment for Order Flow model. These are retro-commission fees that brokers get in exchange for routing their trade orders toward a specific market maker who takes the other side of the order.

This revenue flow is material to some brokers' business models such as Robinhood and Webull. They adapt their features and services to push their client to constantly trade, increasing the average turnover and generating revenue. They promote practices that encompass high trading behavior and lead to risky trading practices. This practice happens regardless of the impact on the user's performance (Costanzo, 2022).

FinTechs have also disrupted the industry, making trading much more accessible and frictionless. Oftentimes, as Robinhood does, providing little complex financial information and creating a game-like brokerage app. This has attracted a peculiar, new kind of retail investor more likely to be influenced by attention (Seasholes & Wu, 2007). For instance, Robinhood users engage in more speculative trading, thereby heightening the likelihood of attention-driven trading (Barber et al., 2022). Further, "attention-grabbing events lead active individual investors to buy stocks they have not previously owned" (Seasholes & Wu, 2007). This translates in a higher likeliness to herd than other retail investors (Barber et al., 2022). The presentation of information, how and which, plays a role in contributing to this outcome.

The change in retail investors' participation level and type has newfound implications for financial markets. The now-famous Gamestock's short squeeze is a good example of that. It also further reflects the importance of social media in influencing retail investors' behavior and its impact on the financial markets (Anand & Pathak, 2022). Some researchers support the fact that social media sentiment, such as Twitter sentiment can be a good predictor of future return, providing new information about analyst's recommendations (Gan et al., 2020; Gu & Kurov, 2020).

Moreover, the existing literature on retail trades is conflicted. The difficulty to access data, often time broker's proprietary data, complicates further analyzing retail investors' behavior. More recent work provided a novel methodology to easily identify retail trade within US equity transaction data (Boehmer et al., 2021). Older work using proprietary data from the NYSE covering some periods over 2000 - 2007 found that retail trade outperformed (Kaniel et al., 2012; Kelley & Tetlock, 2013).
Many other academics disagree with these results. They find that retail investor's active trade underperforms. Their result are consistent over several financial markets, across developed (Barber & Odean, 2000, 2002; Grinblatt & Keloharju, 2000) and developing markets (Garay & Pulga, 2021). More recent work, leveraging recent data from Robinhood supports these results (Barber et al., 2022).

While the outlook of retail investors changed over the past years Robinhood users particularly represent new investors that were not investigated before in the academic literature. They attract younger, smaller, and computer-savvy investors, though less financially educated (Welch, 2022). The average amount of stock owned by users at all times is very low, on average around three positions (Welch, 2022). The average account size is estimated to be as low as $4,500, way below its older and more established competitors (Salzman, 2021). In March 2021, the company had over 18 million funded accounts (Salzman, 2021). These investors are particularly active with turnover several times higher than competitors' clients. In Q1 2020 Robinhood users «traded nine times as many shares as E-Trade customers, and 40 times as many shares as Charles Schwab customers, per dollar in the average customer account in the most recent quarter» (Popper, 2020).

Robinhood investors' decisions can be perceived as following a «crazy mob» narrative. For instance, cannabis stocks were particularly popular among RH investors, with weights several times Market Value weights (Welch, 2022). These investors tend to engage in more attention-induced trading. For instance, they invest in stocks displayed in the 'Top movers' list, namely the 20 stocks with the largest absolute value daily return (Barber et al., 2022). They also have a much higher likeliness to herd at an individual level, leading to significant negative abnormal returns (Barber et al., 2022). Welch (2022), makes the interesting point of arguing that even

though these results hold at the individual level, they may be misleading because the average RH user's investment decisions were much saner and that looking at them together they tend to have a good performing portfolio. This is where the concept of crowd portfolio comes from. When you look at users' holding conveying information in the form of a consensus portfolio, at the aggregate level, considering them as a crowd, the crazy mob narrative doesn't hold because this portfolio performs well according to Welch (2022).
More studies investigating RH investors have emerged including interest in Socially Responsible Investing (Moss et al., 2023), their impact on stock liquidity during the 2020 Covid's market crash (Ozik et al., 2021), trading reaction to intraday price change (Ardia et al., 2023), and specialized ETF tracking attention-grabbing themes (Ben-David et al., 2023), among others.

My research focuses extensively on Welch's (2020) paper. I reproduce the main results and extend them based on results discussed in Fedyk (2023) that pointed out discrepancies in the performance of the ARH portfolio across time. Together these two papers are the basis for my investigation.

2 Data & methodology

2.1 Data

The main data source I use is the Robintrack (RT) data set. Initiated in 2018, it is essentially an hourly script that collected data from Robinhood's public API for approximately two years, from May 5th, 2018, to August 13th, 2020. In August 2020, Robinhood stopped sharing investors' data on the basis that it could participate in day trading and expose Robinhood to negative media exposure. To this date, June 2024, the API is not running anymore. The collected data during this time is still downloadable for free on RT website. The data collection involved downloading this publicly available information, resulting in a database of 3.5 GB, including 8,597 different tickers. This corresponds to intra-hour data of, for each ticker, the amount of RH investing holding that security. Following Fedyk (2023) methodology, I set the daily value for each stock to be the last available count of investors before the end of the trading day, 4 PM EST.

Once I remove the tickers with multiple share classes, those with no positive investors count during the entire period, and incorrect tickers, I am left with 8,459 tickers.

Following Welch's (2022) methodology, I consider only the data starting in June 2018 and discard the data from May 2018. Of these, 3,747 are matchable to CRSP[1] share code 10 and 11 which correspond to ordinary public US Equities. This subset of the RT data is the subject of my paper.

Overall, 94% of RH's tickers can be matched to CRSP and 95% of the tickers for US Equities stocks available in CRSP can be matched to RH tickers at the end of the sampled data. This exhibits a strong coverage of market securities and that the investment universe available to RH users is close to the whole public market for US Equities. Other security types available in the RT data which will not be in the scope of my analysis consist of foreign stocks, US mutual funds, ADRs, REITs and ETFs (Fedyk, 2023). Other security types available to RH users are not available in the RT dataset. This includes options and cryptocurrencies.

Some further caveats with the data from RT is to be pointed out. Robinhood faced system-wide outages on two different days in March 2020. Further, the RT script did not work on three different occasions, totaling 12 days where the data was not available over the 27 months of data.

Finally, having only aggregate level data of investment level in terms of investors' headcount per security tickers we can't have meaningful insight at the individual investor level. Indeed, the average account size is estimated to be as low as $4,500 (Salzman, 2021) and the average stock holding is only 3 stocks per RH investors in August 2020 (Fedyk, 2023). This shapes the way I define weights and use this data.

Regressors used to conduct performance significance tests as explained in the next subsection are from the Kenneth R. French data website (*Kenneth R. French - Home Page*, 2024).

2.2 Methodology

I look at a representative portfolio of all RH investors together. I will assess RH's users' portfolio-level holding with weights defined as $W\text{i} = \frac{Ni}{\sum_{i=1}^{n} Ni}$ in each security, where i is a given stock and N_i is the number of RH holders in this security. Wech (2022) named this portfolio the ARH portfolio while Fedyk (2023) discusses it as a dollar method. I will stick to ARH naming

[1] University of Chicago stock price data base.

from here onwards. This portfolio can be viewed as a consensus portfolio or a "crowd of wisdom portfolio" as termed by Welch (2022). In this weighting, each investor represents a Dollar investment in a stock. This means that regardless of the price of the stock a set amount of investors will have the same impact on the ARH weight whether the price of the stock is $10 or $1000.

For example, let's take a two-stock portfolio where 10 Investors hold stock A of Price 100 and 1 Investor holds stock B of Price 1000. The ARH weight in A would be ${}^{10}/_{11} = 90.9\%$ while a value-weighted portfolio would be 50% in each stock.

An alternative would be to use a shared price-based portfolio, meaning that $W\mathrm{i} = \frac{Ni*Pi}{\sum_{i=1}^{n} Ni*Pi}$ in each security, with P_i the price of the security i. It is coined in Fedyk (2023) as the "share method". However, she finds consistent results regardless of the method used. Further, these portfolio weights will correlate with any variable correlated with price. RH introduced the possibility to buy fractions of shares for its users on December 12th, 2019. This renders the price of stocks as less relevant for defining ARH portfolio composition.

I will test for the significance of the abnormal returns of the portfolios I discuss. I will provide results in three ways. The 0-F benchmark is the mean return (net of the prevailing risk-free rate). The 1-F benchmark is the CAPM's alpha and loadings. The 6-F benchmark is the Fama and French (2015) five-factor model plus momentum. For the latter, I provide factors loading and alpha. For each of these abnormal return metrics, I will provide a T-test to test the significance of the alpha. The null hypothesis is that $\beta_0 = 0$ and the alternative hypothesis is that $\beta_0 \neq 0$. I provide both T statistics and p-values.

3 ARH Crowd portfolio

3.1 ARH portfolio performance

At the time of the data sample, Robinhood's API was available live with intra-hour updates. Therefore it was possible to trade on this ARH portfolio but it is not a representative portfolio of the average individual investor.

Table 1 presents the abnormal return performance of the ARH portfolio using different frequencies, with and without delay. Delays refer to weight construction and investment timing.

I present the performance with a five-day delay before investing for daily rebalancing and a three-month delay for monthly rebalancing. The results with no delay are same-day (month) data, corresponding to end-of-day (first day of the month) portfolio construction. Panel B, C, and D are easy to implement and do not present look-ahead bias.

Following Welch (2022) it uses known methods of portfolio evaluation developed by Fama-French and Carhart. 6-F stands for the 5 Fama-French model and Momentum. The 1-F benchmark is the CAPM only while 0-F is only the mean return net of the risk-free rate.

Panel A of Table 1 presents the average daily performance of the ARH portfolio of 11.9 basis points (bp) per day net of the risk-free rate. However, half of this performance is explained by its market exposure. After taking into account a market Beta of 1.13 the daily alpha goes down to 5.9 bp, significant at a 10% level. More interestingly, once taken into account the 6-F the abnormal return increases back to 7.2 bp daily. This is approximately 19% compounded annually.

Panel B looks at the daily performance using a 5-day delay on the portfolio formation. Contrary to Welch's result, I find that ARH portfolio daily Alpha is not persistent to delay under a 6FF regression where the 3.9 bp alpha is not significant at a 10% level. This is a surprising result given that, he argues, weights are somewhat stable over time.

Panel C is looking at ARH performance with monthly rebalancing. Here there is no delay but I construct the weights at the beginning of the month while the performance is observed throughout the month. A monthly ARH portfolio is easier to implement and should incur little transaction cost. It shows an average monthly return of 1.97%, again largely explained by its market loading. Once regressed on 6FF, the Alpha is still a significant 1.23% at a 10% level. Particularly, it is persistent to delay. Panel D presents the same portfolio, constructing weights with a 3-month delay and its 6FF regressed Alpha is 1.15%, also significant at a 10% level.

These results suggest that an ARH portfolio performed particularly well during the period from June 2018 to mid-August 2020. It is important to note here that this assumes a constant level of dollar investment across time. This indicates that this result understates the actual performance of an ARH portfolio. This is further enhanced by the good timing capabilities of RH investors according to Welch (2022).

Panel A. Daily Rebalancing, No Delay				Panel B. Daily Rebalancing, Five-Day Delay			
	0-F	1-F	6-F		0-F	1-F	6-F
alpha	0.1186	0.0589	0.0719	alpha	0.0836	0.0254	0.0391
(T)	(1.406)	(1.688)	(2.872)	(T)	(1.011)	(0.724)	(1.447)
$P>\|t\|$	*0.16*	*0.092*	*0.004*	$P>\|t\|$	*0.312*	*0.469*	*0.148*
XMKT		1.1334	1.0369	XMKT		1.1051	1.0169
SMB			0.4459	SMB			0.4593
HML			-0.1243	HML			-0.1147
RMW			-0.2263	RMW			-0.2221
CMA			-0.4845	CMA			-0.4404
MOM			-0.356	MOM			-0.2919
555 Days (June 1, 2018 to August 14, 2020)				550 Days (June 7, 2018 to August 14, 2020)			

Panel C. Monthly Rebalancing, No Delay				Panel D. Monthly Rebalancing, 3-Mo Delay			
	0-F	1-F	6-F		0-F	1-F	6-F
alpha	1.9722	0.5059	1.2297	alpha	1.7678	0.5226	1.1475
(T)	(1.236)	(0.848)	(1.979)	(T)	(1.026)	(0.956)	(1.782)
$P>\|t\|$	*0.227*	*0.405*	*0.062*	$P>\|t\|$	*0.316*	*0.349*	*0.093*
XMKT		1.2908	1.1121	XMKT		1.2684	1.1361
SMB			0.9542	SMB			0.6964
HML			-0.3675	HML			-0.2481
RMW			-0.5105	RMW			-0.4637
CMA			0.1522	CMA			0.0759
MOM			-0.141	MOM			-0.1065
27 months (June 2018 to August 2020)				25 months (August 2018 to August 2020)			

Table 1: Return of the ARH portfolio, in %

The ARH portfolio weights are based on the number of RH investors in each stock $W\mathrm{i} = \frac{Ni}{\sum_{i=1}^{n} Ni}$. The table shows the (net of risk-free) 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 and French (2015) five-factor model plus momentum. The weights in panel C are defined at the beginning of the month while returns are computed throughout the month. T-tests are testing for the significance of the estimated Alpha. $\mathrm{H}_0: \beta_0 = 0$; $\mathrm{H}_1: \beta_0 \neq 0$.

3.2 QRH proxy

Welch (2022), tried to characterize the ARH portfolio by describing its correlative determinants to explain the nature of this portfolio and better understand its performance. He used the result to create a quasi-RH (QRH) portfolio that would be useful as a proxy for the ARH portfolio. The most correlated portfolio he found was one constructed with share-trading volume combined with dollar-trading volume. He constructs each weight based on the past 12 months' volume data. First by turning each variable into a weight similar to the ARH weight construction: $W\mathrm{i} = \frac{Vi}{\sum_{i=1}^{n} Vi}$ with V_i the volume metric of stock i. Then weighting the two metrics as a two-third volume and one-third Dollar Volume.

Appendix Table A1 presents the return performance of the QRH portfolio similarly to Table 1, with the same 2018 to 2020 sample, with daily and monthly rebalancing as well as with and without delay. None of the 6FF alpha are significant at a 10% level. However, I note that with daily rebalancing and no delay, panel A, the daily 6F's alpha is 2.5 bp with a p-value of 11%. Particularly, while this QRH portfolio doesn't overperform compared to its risk loading it has an average daily return of 6.2 bp without delay and 0.83% monthly.

More interestingly, the monthly returns series of the ARH and QRH portfolios correlates at 96.84%. It seems to confirm Welch's analysis that volume is a good predictor of ARH weight and that they tend to tilt heavily towards stocks that experienced large past 12 months trading volume.

I continue this analysis with Table 2 where I reproduce Panel C and D from Table 1 but I also regress on the QRH portfolio returns on top of the 6FF regressors.

Table 2 shows that the monthly alpha taking into account the 6FF and QRH is a significant 1% at a 5% level. This is down from 1.23% from table 1, panel C, when I regressed on 6FF only. This seems to indicate that only 18% of the abnormal return, above the 6FF factors was related to trading on volume.

This shows that while volume is a good proxy for characterizing ARH portfolio, volume is not a major contributor to ARH portfolio performance. 82% of the abnormal return is still associated with unidentified skill or luck. As a crowd, RH investors know better how to invest than a naive two-attribute QRH portfolio.

Panel A. Monthly Rebalancing, No Delay		Panel B. Monthly Rebalancing, 3-Mo Delay	
	6FF + QRH		6FF + QRH
alpha	1.0052	alpha	0.9187
(T)	(2.159)	(T)	(1.725)
P>|t|	*0.044*	*P>|t|*	*0.104*
XMKT	-0.132	XMKT	0.1191
SMB	0.3178	SMB	0.1778
HML	-0.3078	HML	-0.1916
RMW	-0.1409	RMW	-0.1954
CMA	-0.2785	CMA	-0.2881
MOM	-0.0352	MOM	-0.0083
QRH	1.1052	QRH	0.8319

Table 2: Return of the ARH Portfolio using QRH as a regressor, in %

The table explores the QRH portfolio return as an independent factor explaining the ARH rate of return. The ARH portfolio weights are based on the number of RH investors in each stock $W\text{i} = \frac{Ni}{\sum_{i=1}^{n} Ni}$. The table shows the (net of risk-free) return performance of the ARH portfolio with respect to the 6-F benchmark and QRH portfolio. QRH is one year, two-thirds a number-of-shares trading volume variable mapped into a weight as $W\text{i} = \frac{Vi}{\sum_{i=1}^{n} Vi}$ and one-third a dollar trading volume variable $W\text{i} = \frac{Di}{\sum_{i=1}^{n} Di}$. The weights in panel A are defined at the beginning of the month while returns are computed throughout the month. Panels A and B are analogues to Panels C and D in Table 1. T-tests are testing for the significance of the estimated Alpha. $H_0 : \beta_0 = 0$; $H_1 : \beta_0 \neq 0$.

4 ARH Investors and the Covid-19 Pandemic

4.1 Covid-19's influence on retail ownership

The data related to RH investors is unique and stands out in two distinct ways. On one hand, as discussed at length during the introduction, RH investors represent a newly emerging type of retail investors that present different investment behavior than the previously studied retail investor. On the other hand, the sample finishes at the onset of the Covid-19 pandemic. It is particularly interesting because the existing literature on retail investors doesn't include a sample that encompass steep market declines such as the 2000 dot-com bubble or the sub-prime crisis of 2008[2]. This creates an opportunity to analyze how RH retail investors adapt in the face

[2] At least in developed countries. There is at least one exception, Garay and Pulga (2021), uses a novel sample from 2006 – 2016 of the Colombian Stock Exchange.

of a sharp market wide downturn and its quick recovery. While this precipitous market decline is insightful it can't be taken as representative of other crises. Particularly, I will discuss in this subsection how the conditions surrounding the covid crisis may have influenced RH retail investors. Finally, I will discuss in the next subsections, how this crisis may question the reliability of the result discussed in the previous section and also presented by Welch (2022).

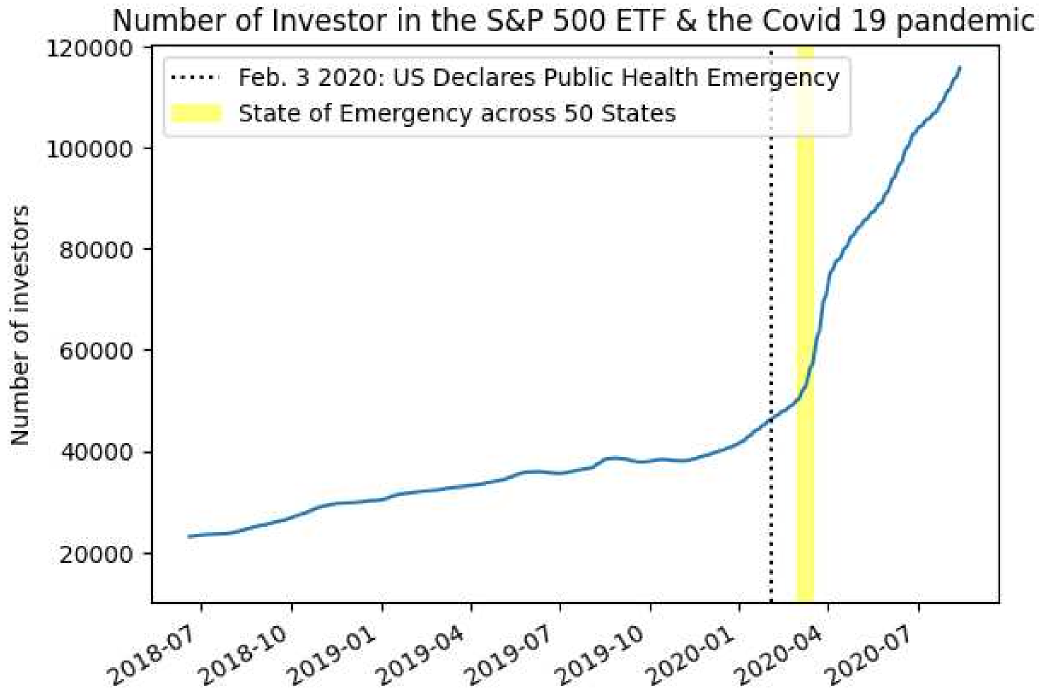

Figure 1: Number of Investor in the S&P 500 ETF & the Covid-19 pandemic

The blue line represents the number of investors in the S&P500 ETF from 2018 to 2020. The dashed black line represents the day that the US declared Covid-19 a public health emergency on February 3rd 2020. The area highlighted in yellow represents the period over which declarations of state emergency were made in the different 50 states shortly followed by stay-at-home orders for most of them. The figure shows that the amount of RH investors increased simultaneously to the start of the Covid-19 crisis.

The Covid-19 pandemic is associated with a large increase in the RH user base. Figure 1 presents the amount of RH investors in the S&P 500 ETF over the 2018 – 2020 sample. I'm using it as a proxy to estimate the increase of RH holding throughout the sample. The result I present is consistent with other measures presented in Welch (2022) and Fedyk (2023).

The blue line presents the total headcount of investors in the S&P500 ETF over time. The dashed line, on February 3rd, 2020 is the day that the US declared the Covid 19 as a public health emergency. The area highlighted in yellow represents the period over which declarations of state emergency were made in the different 50 states shortly followed by stay-at-home orders for most of them.

Further, US stimulus check program gave out three payments ($600, $200, and $1200) for annual income earners below $60,000. While two of these three payments occurred after the end of RH sample data it may have affected RH retail investors' market participation given the average account size of only $3,500.
This figure demonstrates a strong association between the increase in RH user base and the Covid-19 onset. This 300% increase between February and August 2020 is likely related to stay-at-home orders, and increased media scrutiny associated with increased free time. It is further postulated by Ozik, Sadka, and Chen (2020) that the lockdown may have potentially been a contributing factor. Interestingly, on the basis of Robinhood's 10-K statements and as collected by Fedyk (2023), we know that this increasing trend kept going up until 2021 with 5.1M funded accounts in 2019, 12.5M in 2020, 22.7M in 2021, and 23M in 2022.

4.2 Yearly breakdown results analysis

This analysis of how material the Covid-19 crisis is to this sample brings me to re-examine the results previously introduced in Section 4, also presented by Welch (2022). Indeed, the performance of the ARH portfolio largely differs depending on the sample I use. Table 3 presented the 6FF regression from Table 1 Panel A on the Pre-2020 sample, 2018 and 2019, and the 2020 sample separately.

The results are very interesting and bring in a different interpretation than discussed in section 4. The same regression in the sample ranging from June 2018 to December 2019 gives a non-significant alpha at a 10% level with a large p-value of 0.34. However, the 2020 sample that includes only 156 observations presents a very significant daily alpha of 18.5 bp at a 1% level. This means that all, or most, explanatory effect of the full sample regression is induced by abnormal returns occurring in 2020 and the Covid-19 onset.

	2018 & 2019	2020	Full sample
Number of observations	399	156	555
alpha	0.0186	0.185	0.0719
(T)	(0.955)	(2.653)	(2.872)
$P>\|t\|$	*0.34*	*0.009*	*0.004*
XMKT	1.1277	1.0152	1.0369
SMB	0.3373	0.4941	0.4459
HML	-0.2201	-0.1358	-0.1243
RMW	-0.1922	-0.3511	-0.2263
CMA	-0.2479	-0.4214	-0.4845
MOM	-0.1896	-0.4456	-0.356

Table 3: Yearly breakdown of the ARH Portfolio performance, in %

The table presents a 5FF plus Mom (6FF) regression of the data for public US Equities underlying over different periods. 2018 data starts on June first, and 2020 data ends on August 14th. The number of observations corresponds to the amount of day-return available on which the factors are regressed. T-tests are testing for the significance of the estimated Alpha. $H_0 : \beta_0 = 0$; $H_1 : \beta_0 \neq 0$. The table shows that the abnormal return in the full sample is mostly explained by large overperformance in 2020.

Table 4, delves into the ARH and QRH portfolio annual breakdown and performance statistics. It shows that in terms of performance compared to its benchmark, the ARH portfolio did poorly in 2018, performed 9 percentage points better in 2019, and much better in 2020, overperforming its benchmark by 34 percentage points. Most of the over-performance compared to the market benchmark is indeed due to the 2020 performance. Finally, while the performance of the ARH portfolio is more volatile than its market benchmark its overall Sharpe ratio is more than twice the benchmark's.

	2018 (7 mo.)	2019 (12 mo.)	2020 (8.5 mo.)	All	All (ann.)	SD (ann.)	Sharpe Ratio
ARH Portfolio - rf	-10.66%	36.68%	41.57%	72.88%	26.98%	31.53%	0.86
Benchmark - rf	-8.78%	27.71%	7.05%	24.70%	10.11%	25.33%	0.40
QRH Portfolio - rf	-15.56%	28.46%	17.09%	27.01%	11.00%	30.73%	0.36

Table 4: ARH & QRH portfolio annual return and performance statistics

Cumulative return of the respective portfolio over the length of data available. 2018 data starts on June first, and 2020 data ends on August 14th. The table presents annual returns and statistics over different time periods. The benchmark presented is defined as market return by Fama and French (2023): " The market return for month t is […]the value-weight return on all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have (i) a CRSP share code of 10 or 11[…]" . Essentially, it corresponds to a value-weighted of all the stocks available in CRSP which is approximately the investment universe available to RH investors.

This questions the relevance of the results presented before and by Welch (2022), further inviting an investigation of what could have led to such a performance. This will be the subject of the next two sub-sections.

4.3 Contrarian investment during the Covid-19 onset

The Covid onset has seen many bursts and booms. The S&P500 fell by 33% in a month between February 19th and March 23rd 2020. The market recovered to 3,000 by the end of May compared to 3,386 on February 19th. Therefore, I have lots of large absolute value returns throughout the period. New RH users continuously poured into the market, de facto contributing to stabilizing its liquidity. «Retail trading attenuated the rise in illiquidity by roughly 40%» during the Covid-19 lockdown (Ozik et al., 2021)[3].

Figure 2 presents RH users' contrarianism in 2020 during the covid onset. I observe that contemporaneous large absolute returns are associated with similarly large increases in holding. This suggests that investors did not retreat from the market even during its starkest decline and contributed to a small market stabilizing role.

[3] This study uses the same data set of Robinhood user to investigate retail investors.

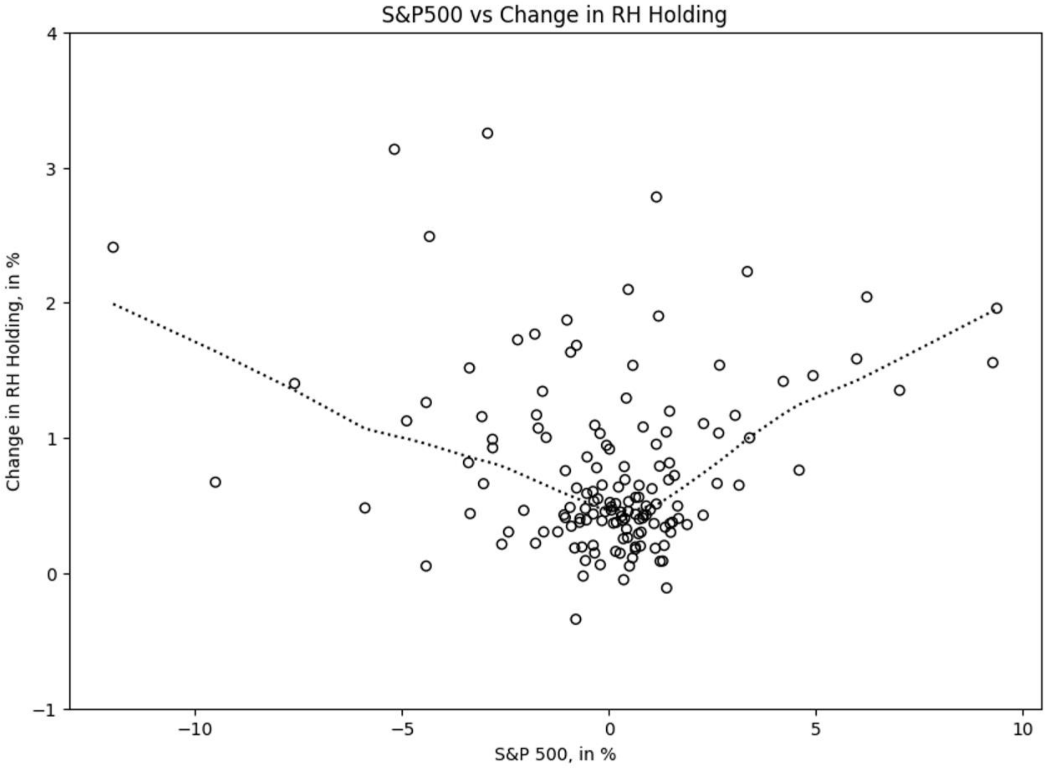

Figure 2: ARH systematic contrarianism in 2020

This figure shows that RH investors' investment in US Equities securities (SHRCD 10 & 11) tends to follow large absolute returns in the S&P500. The plot depicts the daily percentage change in cumulative RH holding against the S&P500 returns. These are same-day data. The line is fitted using the Lowess function (Locally Weighted Scatterplot Smoothing) with a span of 0.75.

However, looking at Figure 3, which pictures the same data on the 2018 - 2019 sample, I infer that this behavior was only contemporaneous to the Covid-19 onset. While extreme absolute value returns were scarce over the sample, large contemporaneous market movements were not associated with a large increase in holding as suggested by Welch (2022). See Appendix 2 for the same figure applied to the whole sample 2018 – 2020[4].

[4] As initially presented by Welch (2022). Figure 2 and 3 come from my own research.

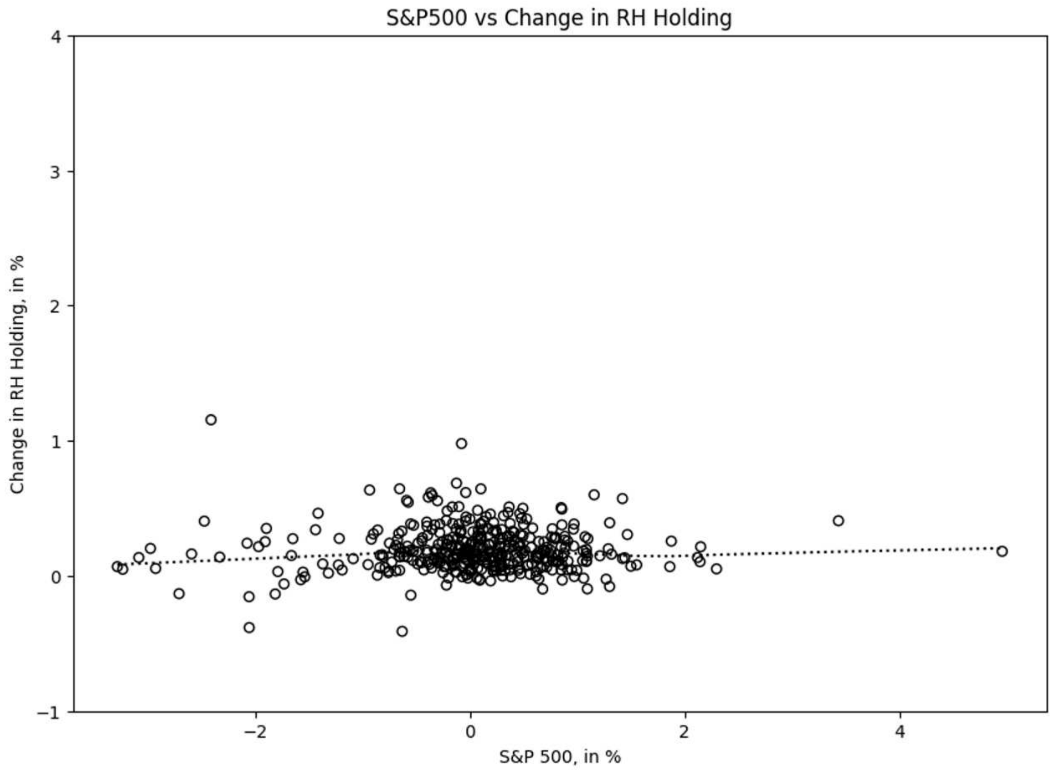

Figure 3: ARH absence of contrarianism in 2018 – 2019

This figure shows that RH investors' investment in US Equities securities (SHRCD 10 & 11) does not tend to follow large absolute returns in the S&P500. The plot depicts the daily percentage change in cumulative RH holding against the S&P500 returns. These are same-day data. The line is fitted using the Lowess function (Locally Weighted Scatterplot Smoothing) with a span of 0.75.

Concluding on this sub-section, ARH contrarianism to market movement in 2020 may have strongly contributed to its performance. While the market crash reflected reasonable expectations of economic depression due to the, at the time, coming pandemic RH users largely benefited from investing in the market during this time period. In this case, as in the previous market crash of US equities, investing in the market during its collapse would have largely paid off.

4.4 Firm-specific response to Large absolute returns

What is consistent throughout the sample however is that RH users tend to invest heavily in firms that observe large absolute value whether positive or negative. This has been the subject of disagreement among the existing literature. Barber et al. (2022) pointed out that RH investors engage in attention-induced trading, participate in herding behavior and foster «average 20-day abnormal returns [of] -4.7% for the top stock purchases each day» (Barber et al., 2022).

In explaining the performance of a similarly constructed ARH portfolio, Fedyk (2023) finds a Buy-The-Dip effect (BTD). He shows that investing following extreme negative returns of large companies results in next-day returns 2.5 times greater than «analogous mean return for the control group stocks» (Fedyk, 2023). However, she also finds that this strategy "ceases to be profitable as soon as the holding period is extended to three days- in this case, BTD stocks perform significantly worse than the control group" (Fedyk, 2023).

Figure 4 replicates these findings. It shows that extreme absolute value return at the firm level is associated with a contemporaneous increase in holding in these firms. These results are consistent throughout the whole sample data.

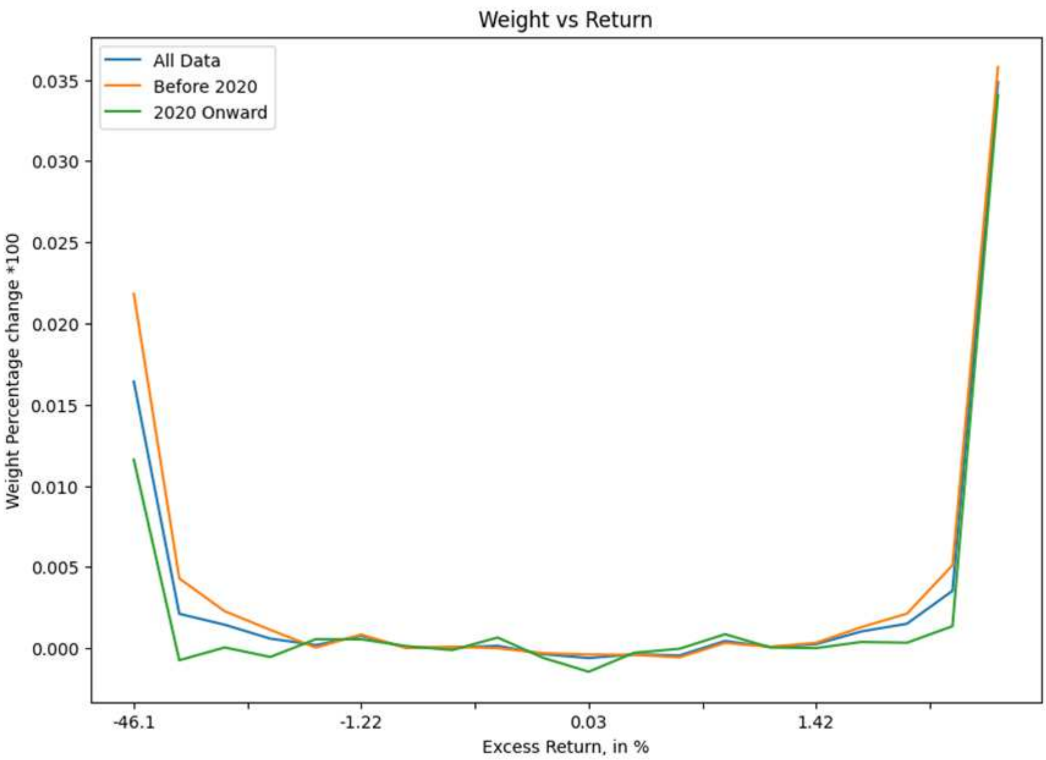

Figure 4: RH holding changes by previous day firm level's net of market rate return.

Stock days are first grouped by Excess Return above the market return in 20 bins based on every 5th percentile cut-off value. Within each bin, the y-axis represents the mean percentage net change in ARH investment weight. The sampled data begins in June 2018 and ends mid-August 2020. The lines simply connect the different conditional averages on each bin for all data (blue), pre-2020 data (orange), and 2020 data (green). This figure shows that, for all samples, extreme absolute value return at the firm level is associated with a contemporaneous increase in holding in these firms.

This BTD effect most likely had a great impact in contributing to the ARH performance during 2020, while it on average had a negative impact throughout the sample.

I also observe a tendency to buy stocks that see large positive returns. Fedyk (2023) points to the fact that this graph's result may be misleading in that RH investments tend to follow high positive returns for small capitalization. This could be due to high media attention. She argues BTD effect could be the reflection of RH investors' willingness to invest in high-brand, well-liked companies perceived as too expensive. This dip is being viewed as a «better opportunity».

5 Conclusion

Robinhood's user base increased significantly and consistently from 2018 to 2020. I challenged Welch's (2022) analysis that the ARH crowd portfolio performed well in the cross-section. I showed that while they indeed earn significant alphas with respect to market factors and the Fama and French five factors plus momentum this was biased by the last few months in the sample. RH investments tilted heavily towards those with above-average trading volume over the previous 12 months. However, this is not enough to explain RH investors' abnormal returns.

This study found that the RH consensus portfolio did not perform well throughout mid-2018 to mid-2020 and that the overall abnormal return is fully explained by large overperformance during the 2020 Covid-19 onset. It did not deter investors' growing interest in the stock market. The pandemic has seen a massive increase in RH retail investors. Collectively they did not panic for which they were rewarded handsomely.

They collectively increased their holding after large market increases or decreases, particularly during the 33% market drop at the beginning of the Covid-19 crisis. They greatly benefited from this. More surprisingly, they showed a strong interest in stocks that saw large absolute value returns. I conjectured that while this most likely contributed to their collective poor performance pre-2020 it contributed positively to their performance in 2020.

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7 Appendix

Table A1: Return Performance of the QRH Proxy Portfolio, in %

This table is analogous to previous tables with ARH excess return as the dependent variable instead of QRH excess return. QRH is two-thirds a number-of-shares trading volume variable mapped into a weight as $W\text{i} = \frac{Vi}{\sum_{i=1}^{n} Vi}$ and one-third a dollar trading volume variable $W\text{i} = \frac{Di}{\sum_{i=1}^{n} Di}$. Weights are defined based on past 12 months volume. The table shows the (net of risk-free) return performance of the QRH 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 and French (2015) five-factor model plus momentum. T-tests are testing for the significance of the estimated Alpha. $H_0: \beta_0 = 0$; $H_1: \beta_0 \neq 0$. The weights in panel C are defined at the beginning of the month while returns are computed throughout the month.

Panel A. Daily Rebalancing				**Panel B. Daily Rebalancing, Five-Day Delay**			
	0-F	1-F	6-F		0-F	1-F	6-F
alpha	0.062	0.0014	0.025	alpha	0.0469	-0.0136	0.0103
(T)	(0.754)	(0.053)	(1.601)	(T)	(0.572)	(-0.533)	(0.665)
P>|t|	*0.451*	*0.958*	*0.11*	*P>|t|*	*0.568*	*0.594*	*0.506*
XMKT		1.1524	1.0732	XMKT		1.1291	1.0703
SMB			0.3365	SMB			0.337
HML			0.0474	HML			0.0507
RMW			-0.2111	RMW			-0.2145
CMA			-0.1954	CMA			-0.1941
MOM			-0.2441	MOM			-0.2387
555 Days (June 1, 2018 to August 14, 2020)				555 Days (June 7, 2018 to August 20, 2020)			

Panel C. Monthly Rebalancing				**Panel D. Monthly Rebalancing, 3-Mo Delay**			
	0-F	1-F	6-F		0-F	1-F	6-F
alpha	0.8305	-0.6994	0.2211	alpha	0.6205	-0.6991	0.126
(T)	(1.602)	(-1.716)	(0.525)	(T)	(0.348)	(-1.694)	(0.288)
P>|t|	*0.609*	*0.099*	*0.605*	*P>|t|*	*0.731*	*0.104*	*0.777*
XMKT		1.3469	1.2256	XMKT		1.3443	1.2265
SMB			0.6269	SMB			0.5026
HML			-0.0588	HML			-0.0318
RMW			-0.3641	RMW			-0.3142
CMA			0.4243	CMA			0.3592
MOM			-0.1042	MOM			-0.1344
27 months (June 2018 to August 2020)				26 months (August 2018 to September 2020)			

Figure A2: ARH contrarianism in 2018 – 2020:

This figure shows that RH investors' investment in US Equities securities (SHRCD 10 & 11) across the whole sample tends to follow large absolute returns in the S&P500. The plot depicts the daily percentage change in cumulative RH holding against the S&P500 returns. These are same-day data. The line is fitted using the Lowess function (Locally Weighted Scatterplot Smoothing) with a span of 0.75.