# 1 Introduction

In recent years, the rise of commission-free trading platforms has profoundly reshaped retail investor behavior and sparked growing interest among scholars in behavioral finance. One of the most prominent examples is Robinhood, a mobile-first brokerage that gained widespread popularity for eliminating trading fees and offering a highly gamified user experience. The platform attracted a large number of retail investors, particularly young and inexperienced individuals. [1]

An important development in the empirical literature was the release of Robintrack, an open-source dataset that tracks the number of Robinhood users holding individual stocks over time. This data, which was collected via Robinhood's public API, provides a rare opportunity to directly observe the trading dynamics and portfolio shifts of real retail investors. The dataset can be downloaded from https://robintrack.net/.

Several recent studies, including [Fedyk, 2024] and [Welch, 2022][2], have leveraged the Robintrack dataset to examine retail investor performance. Their findings suggest that Robinhood investors—contrary to popular belief—exhibited strong market timing and outperformed passive benchmarks. In particular, these papers report significant cumulative returns and positive alpha using standard factor models.

In this paper, we revisit these claims by constructing an alternative methodology for portfolio formation based on the same dataset. Specifically, we analyze whether the returns of Robinhood users' favorite stocks exhibit stochastic dominance over benchmark indices. Our goal is to offer a more nuanced assessment of whether retail investors truly generate abnormal returns or whether previous results may be driven by sample selection or methodological choices.

# 2 Robinhood Dataset

## 2.1 Description of the Dataset

The dataset records the **number** of Robinhood users holding at least one share of 8,619 securities, with observations taken hourly. Following [Welch, 2022] and [Fedyk, 2024], we aggregate this data on a daily basis by selecting the last observation of each trading day.

[1] According to Robinhood's IPO filing, the typical user on the platform is 31 years old, with an average account balance of approximately $3,500. Notably, around half of the platform's users are investing for the first time.

[2] it must be noted that the former explicitly follows the mehtod of the latter

The sample spans from February 5, 2018, to August 13, 2020, covering 818 days. Note that the dataset includes non-trading days and contains some missing observations.

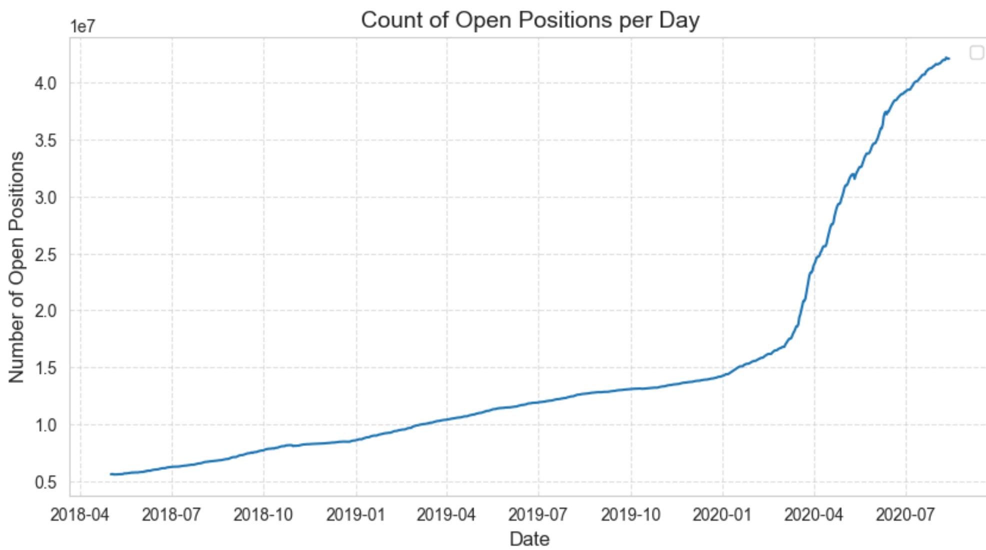
*Since the dataset only provides the number of investors per security, we cannot track individual holdings, monetary amounts, or share quantities. Moreover, buy/sell flows are unobservable; however, we can approximate them using changes in the number of holders.*

We merge this dataset with CRSP to obtain market-level information and later construct a benchmark index. The resulting dataframe contains 7,613 unique securities—substantially more than in [Fedyk, 2024] and [Welch, 2022], who restrict their analysis to U.S. common stocks only. Details of the data cleaning procedure are provided in Appendix B.

In terms of security types, common stocks represent 57.3% of the dataset, while ETFs and other funds account for 26.3% and 8.7%, respectively. Structured products, REITs, and ADRs constitute the remaining share. When classifying by market capitalization, stocks dominate with 83.1%, followed by ETFs (9.3%) and other funds (3.3%).

The total number of open positions on any given day is calculated as the sum of users holding at least one share across all securities—i.e., a row-wise sum across the dataset.

Market data for each security was retrieved from CRSP[3] via WRDS. Out of the full universe, 8,099 securities were available in CRSP, as it includes only U.S.-listed assets.




The figure above shows the daily count of open positions on Robinhood from April 2018 to mid-2020. We observe a steady increase in user participation, with a sharp acceleration

[3]The Center for Research in Security Prices (CRSP), based at the University of Chicago, provides high-quality historical market data widely used in finance research and investment analysis.

beginning in early 2020. This surge coincides with the onset of the COVID-19 pandemic, likely driven by a combination of heightened market volatility, increased retail interest, and fiscal stimulus payments.

# 3 Analysing Trading Patterns

## 3.1 Methodology

### 3.1.1 Weights Methods

[Fedyk, 2024] and [Welch, 2022] use the same approach to build the performance of the Robinhood crowd (or "reference index"): they build daily weights and then apply the weights from the previous day to daily stock returns, directly building portfolio returns.

First, it is necessary to define how those weights are computed. They define two different types of weights, although they yield similar findings in their analysis.

The first method is the "dollar method", which assumes that every investor represents an equal dollar amount investment in the stock.

$$w_{i,t}^{\text{dollar}} = \frac{N_{i,t}}{\sum_j N_{j,t}} \tag{1}$$

where $w_{i,t}$ is the Robinhood portfolio weight of security $i$ at time $t$ and $N_{i,t}$ is the number of investors in security $i$ at time $t$.

Alternatively, they define the "share method", where each Robinhood investor in a stock represents a one share investment in that stock.

$$w_{i,t}^{\text{share}} = \frac{N_{i,t} \cdot P_{i,t}}{\sum_j N_{j,t} \cdot P_{j,t}} \tag{2}$$

where $P_{j,t}$ is the price of stock $j$ at time $t$.

### 3.1.2 Building the Robinhood Portfolio

As explained above, the biggest limitation of the Robintrack dataset is that it counts the number of users holding a certain security and doesn't provide any information on the amount invested in a particular security.

The other authors build the portfolio returns by multiplying weights by their daily returns[4] , assuming that the weights, however computed, represent a certain share of wealth in a stock of the Robinhood crowd.

$$r_p = \sum_{i=1}^{N} w_{i,t} \cdot r_{i,t} \tag{3}$$

On the other hand, I tried to compute the value of the Robinhood portfolio by doing a weighted sum of the prices of the securities in the dataset. Conceptually, this represents the portfolio of an investor who decides to allocate a certain number (or percentage) of shares to each security.

We can therefore define the value of the Robinhood Portfolio as follows:

$$V_{RH,t} = \sum_{i=1}^{N} w_{i,t}^{\text{dollar}} \cdot P_{i,t}$$

Returns are then computed from the value of the overall portfolio.

## 3.2 Comparing Returns and Risk measures

The biggest difference do not appear when using different kinds of weights ("dollar" or "share" method) but rather when building the portfolio from prices or returns. Moreover, Fedyk and Welch build their portfolio only using common american stocks (share code 10 or 11). In my final analysis I look at all types of securities but significant differences emerge even when using the same sample.

As the other authors have claimed in their papers, the Portfolio built directly from returns had a much higher cumulative return.

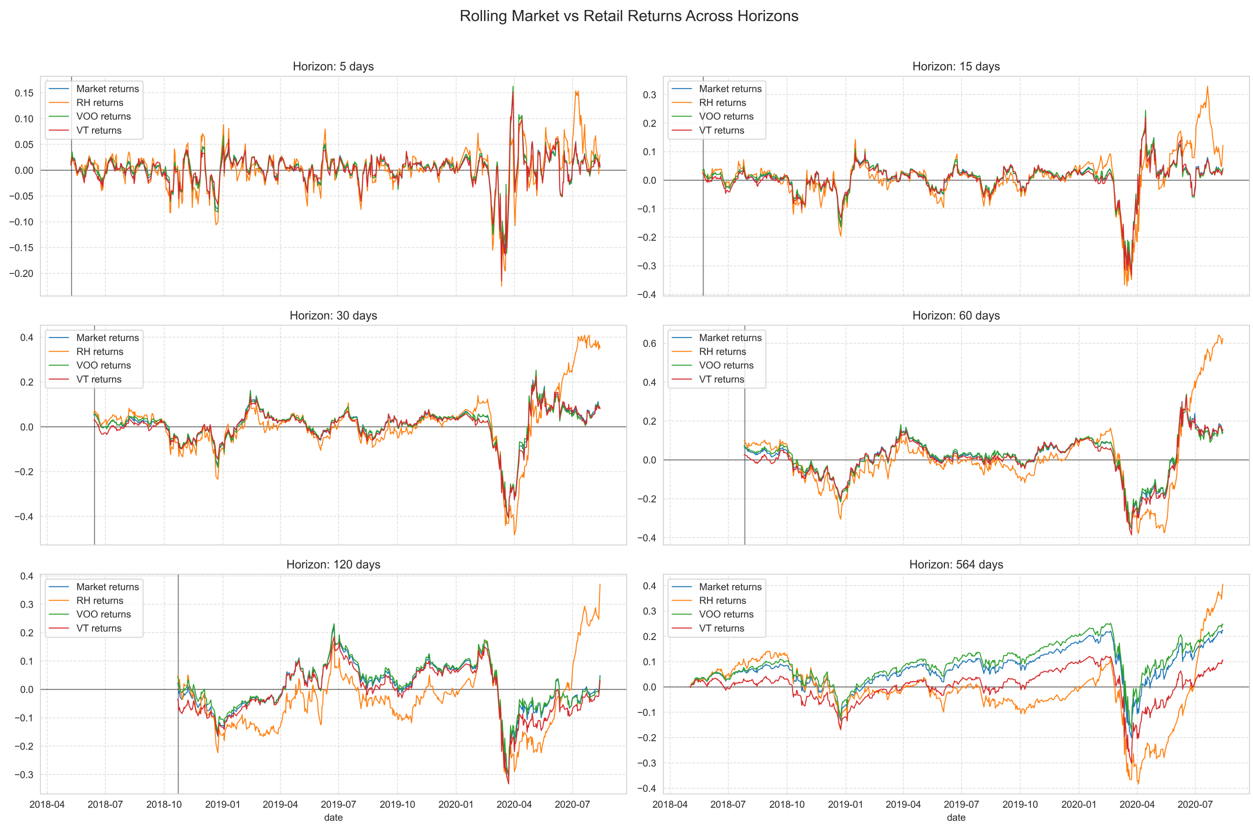
I will proceed to analyse in more detail the distribution of returns of different Robinhood portfolios, showing that my method depicts a far less rosy picture of the "Robinhood strategy".

### 3.2.1 Returns

Returns for a given time frame are computed as the sum of the daily log returns for the previous days.

[4]returns are computed directly by CRSP and are adjusted for dividends, e.g. if $P_0 = 10$ and $D_1 = 5$ and $P_1 = 5$ returns would be 0%

Since there isn't a possible indicator of the average holding period for Robinhood investors, we can compute the moving averages and cumulative returns for all these indices, showing the profitability of the Robinhood portfolio at different time frames.




At short-term horizons (5 to 15 days), all three portfolios show similar patterns, with relatively mild fluctuations. Retail returns exhibit slightly higher volatility, particularly for the Robinhood portfolio, indicating that retail investors are more reactive to short-term market movements. The returns across these horizons reflect a degree of correlation, suggesting that, over short periods, retail investors' behavior mirrors that of the broader market, albeit with more pronounced movements.

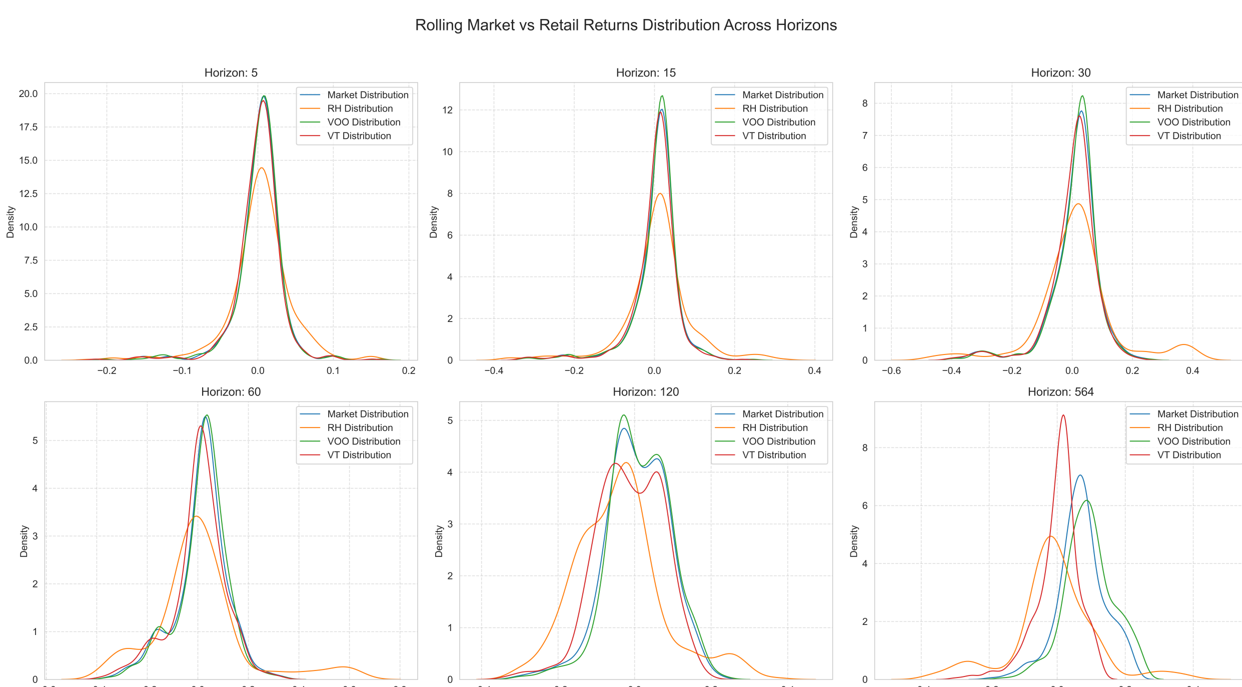
At the 30- and 60-day horizons, divergence becomes more apparent. The Robinhood portfolio shows a higher degree of volatility, with both larger peaks and deeper troughs compared to the market and the ETF benchmarks (VOO and VT). This volatility suggests that retail traders may be engaging in more speculative behavior or reacting strongly to market news, which could lead to exaggerated responses and momentum chasing. Notably, during periods of rapid market movements (e.g., mid-2020), the Robinhood portfolio experiences sharp rallies, likely driven by retail investor participation in tech stocks or speculative assets.

At the 120-day horizon, the Robinhood portfolio begins to underperform relative to both VOO and VT, particularly in major market downturns like the COVID-19 crash. The underperformance during these periods is consistent with the behavior observed in retail investors during market corrections—often driven by overreaction or poor risk management. However, after the COVID market crash, the Robinhood portfolio shows notable recovery, achieving higher returns than VOO and VT, reflecting retail traders' ability to capitalize on post-crash rebounds, potentially due to increased exposure to riskier assets.

At the 564-day horizon, the long-term performance diverges significantly. The Robinhood portfolio initially lags behind both VOO and the market, reflecting a less optimal asset allocation or suboptimal stock selection. While there is some recovery post-COVID, retail investors still fail to capture the consistent growth observed in the broader market over a longer timeframe. This highlights the challenges that retail investors may face in achieving long-term growth, especially when influenced by short-term market sentiment or reacting to news-driven volatility. Nonetheless, the post-crash rally showcases the potential for retail portfolios to outperform during certain market phases, albeit with higher risk.

Overall, the plot demonstrates that while retail portfolios can experience significant short-term gains, their performance is often more volatile and less consistent over the medium to long term, with periods of underperformance and delayed recoveries.

Looking at the distribution of returns for the same periods other insights can be drawn (compare 1).



At shorter horizons (5 to 30 days), the return distributions for all portfolios- market, Robinhood (RH), VOO, and VT- are quite similar, with tightly clustered and symmetric shapes. However, the Robinhood distribution exhibits slightly fatter tails compared to VOO and the market, suggesting that retail investors, particularly those in the Robinhood portfolio, experience more extreme short-term gains and losses. This indicates higher short-term volatility and sensitivity to market movements.

As the horizon increases (60 to 564 days), the Robinhood distribution becomes increasingly dispersed, with wider tails and lower peaks. This shift indicates that retail investors are exposed to higher volatility over longer periods, with greater potential for both positive and negative extreme outcomes. In contrast, VOO and the market distributions remain relatively stable, with tighter and more concentrated peaks. These distributions suggest that diversified portfolios, like VOO and the market index, provide more consistent and lower-risk returns over time.

At the longest horizon (564 days), the Robinhood distribution shows a noticeable left skew, indicating that the portfolio underperforms over the long term. This is consistent with earlier findings of long-term underperformance, where retail investors fail to capture consistent gains in the broader market. In contrast, the VOO distribution is shifted rightward, reflecting stronger and more consistent long-term performance, which is typical of diversified, lower-risk portfolios.

In summary, these distribution plots highlight the increased volatility and higher risk exposure associated with the Robinhood portfolio, especially as the time horizon lengthens. Over both medium and long horizons, retail portfolios are more prone to extreme outcomes, with consistent underperformance relative to the more diversified VOO and market portfolios. This reinforces the conclusion that retail investors, while potentially benefiting from short-term rallies, struggle to maintain consistent returns in the long run due to greater sensitivity to market fluctuations and suboptimal asset selection.

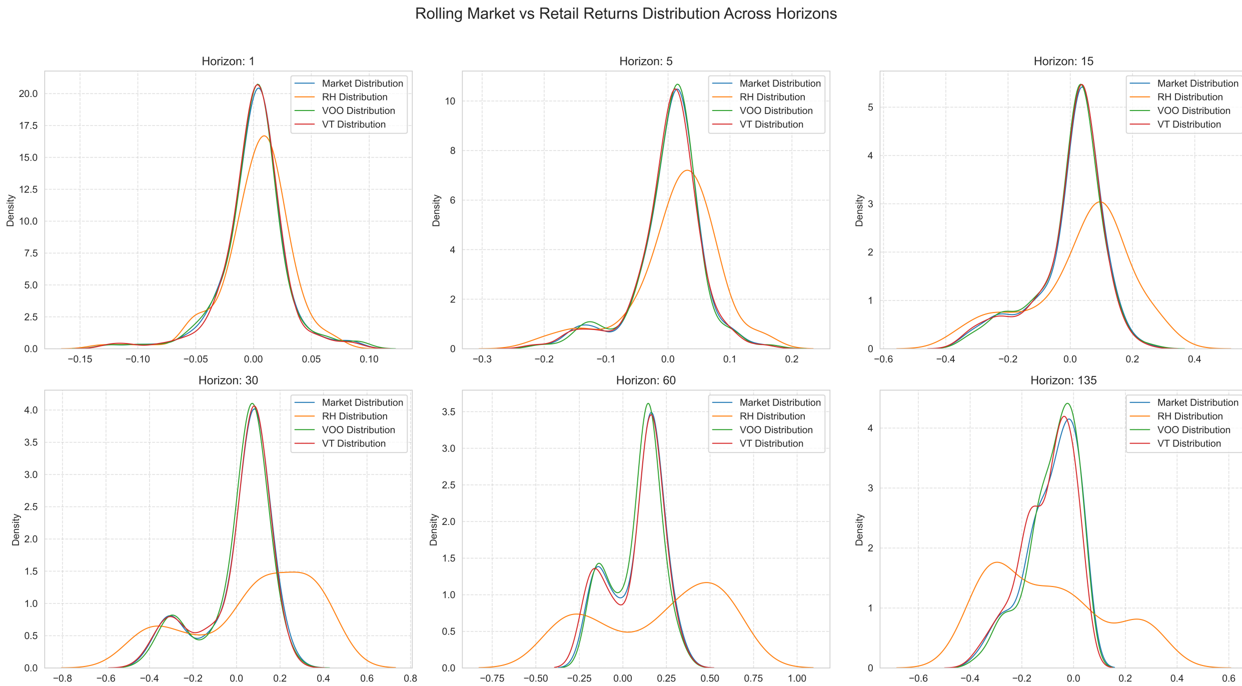
**What Happened during the Pandemic?** Analyzing the same indices from February 3rd, 2020 we can find some relevant insights.

At very short horizons (1-5 days), performance across all portfolios is similar and volatile, with no consistent pattern. However, from the 15-day horizon onward, a clear divergence emerges: Robinhood portfolio returns (orange) begin to outpace both the market indices, which have a high degree of correlation.

This trend becomes particularly evident at 30, 60, and 135-day horizons, where the Robinhood portfolio exhibits significantly higher cumulative gains after a more sluggish start. In


contrast, VOO and the market index recover more gradually, with smoother return paths and lower cumulative gains. This reflects broader diversification and reduced exposure to speculative stocks.

We can look at the distributions of returns for this timeframe as well:



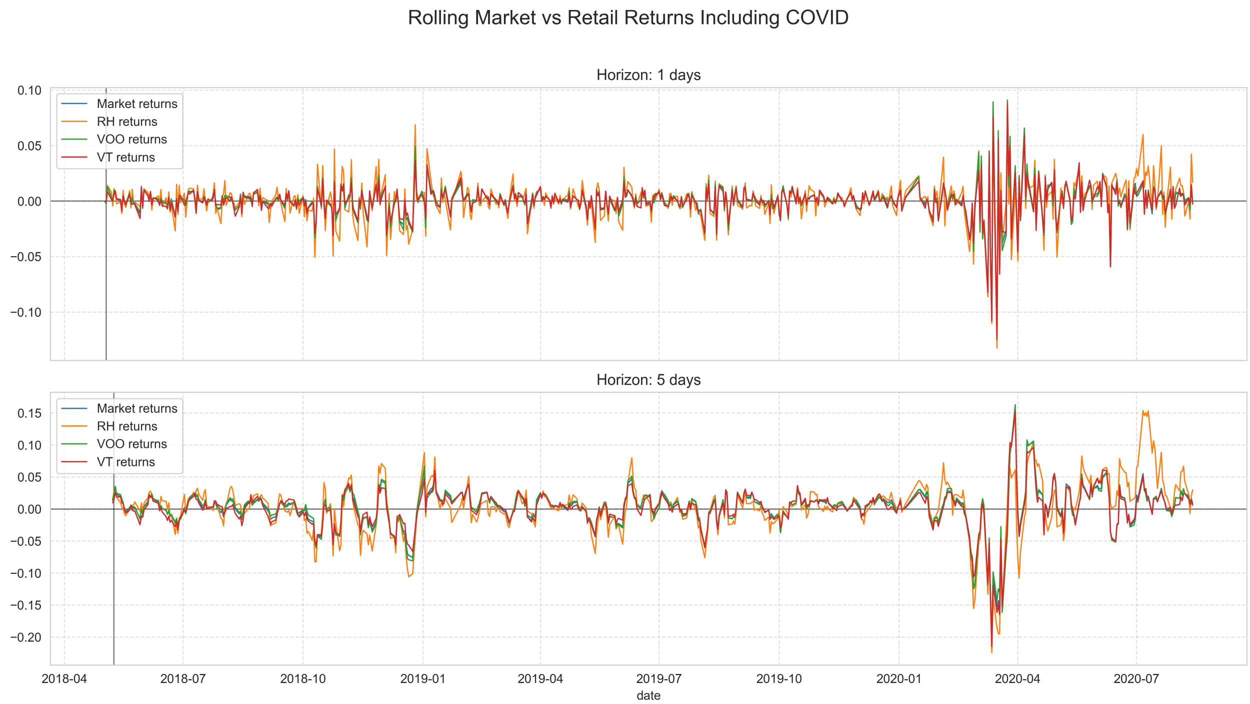

## 3.3 Analysis of Short-Term Market Movements and Volatility, Including the Impact of COVID

### 3.3.1 Return Characteristics and Volatility Analysis

**including COVID** Comparing the daily and 5-day moving average returns for the whole period available we observe really similar behavior in terms of returns and distributions for the marker indices, while RH has significantly fatter tails (which can be observed also in the CDF plot).

RH has slightly higher average returns compared to the market (MC) both for 1-day and 5-day returns. For 1-day returns, RH has an average return of 0.000719, which is higher than the market's 0.000396. Similarly, for 5-day returns, RH's average is 0.003281, which is again higher than the market's 0.001913. In terms of standard deviation, RH shows more volatility in both horizons. The 1-day standard deviation for RH is 0.018809, compared to the market's 0.01547, and for the 5-day returns, RH's standard deviation is 0.041909, while the market's is 0.031198. Therefore, RH consistently exhibits higher returns and higher volatility over both timeframes compared to the market. Detailed distribution are in table 2.

Here below the plots of the time series:




**Before COVID** Excluding returns from February 3rd 2020 might help to reduce some of the noise in the sample and allow us to understand more significant trends about RH investors.

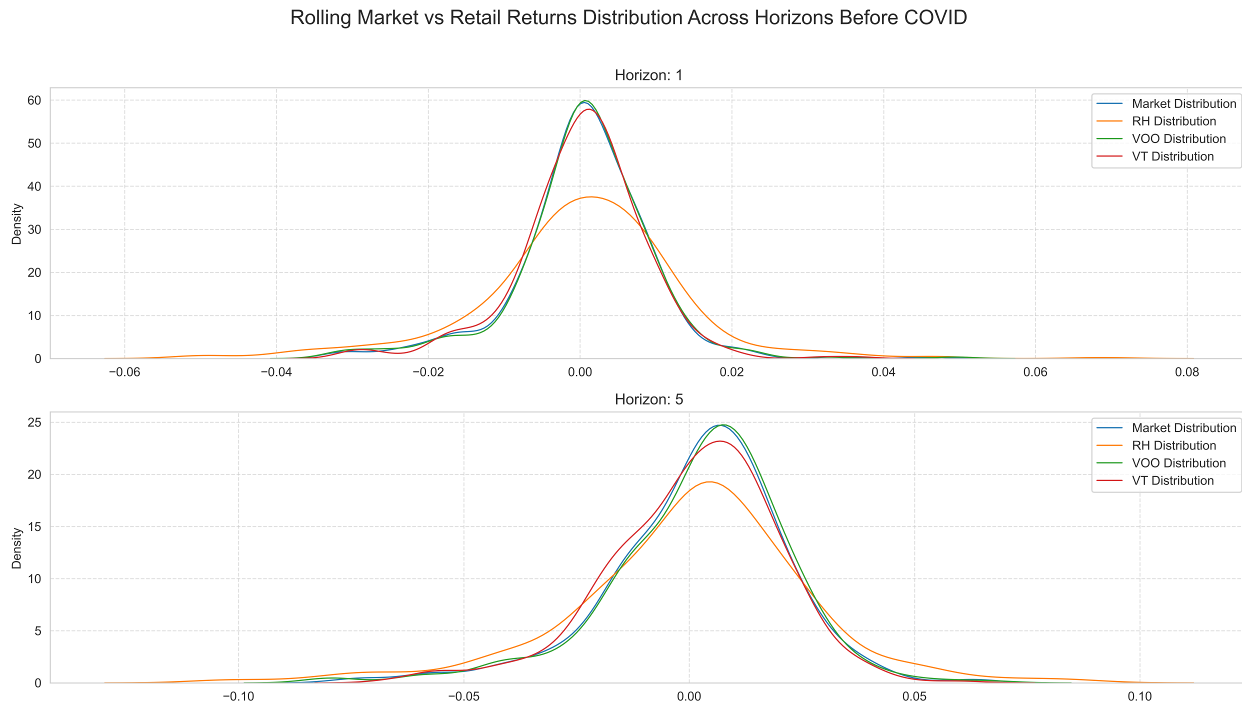
For 1-day returns, RH still has lower average returns compared to the market (MC). RH has an average return of 0.000115, while the market's average is 0.000419.

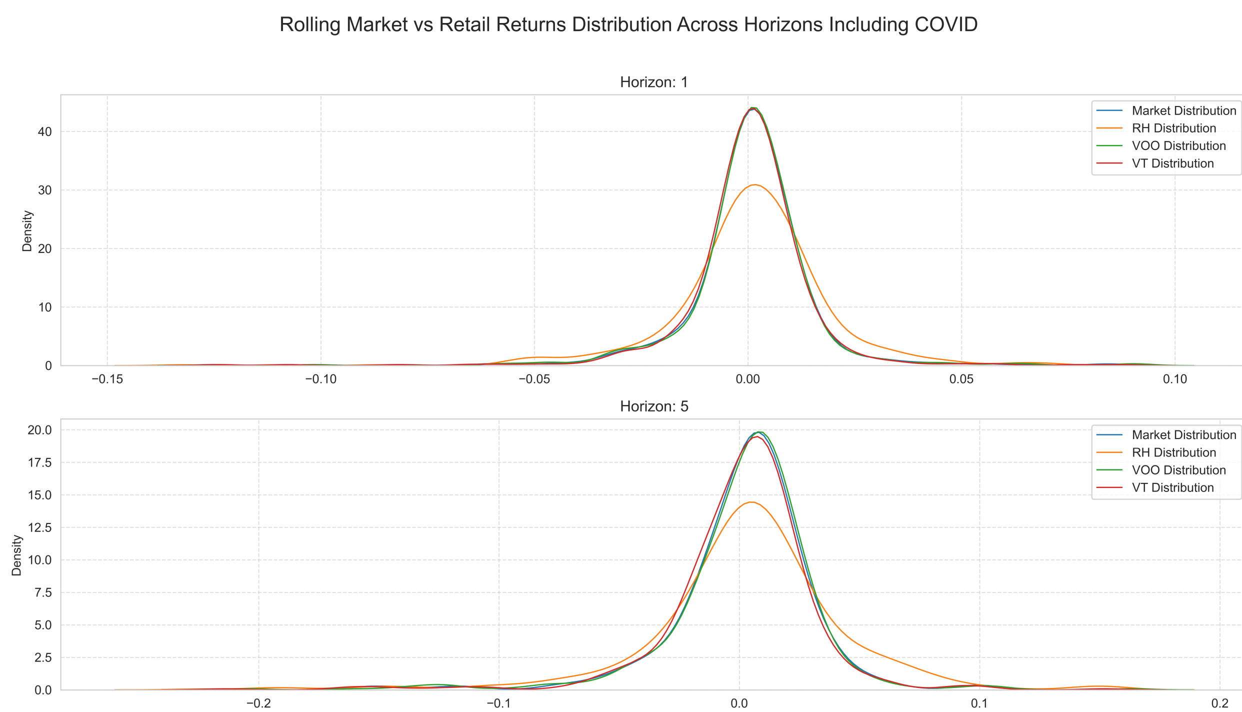
For the 5-day returns, RH's average is much smaller than that of the market. RH has an average return of 0.000259, while the market's average is 0.002091.

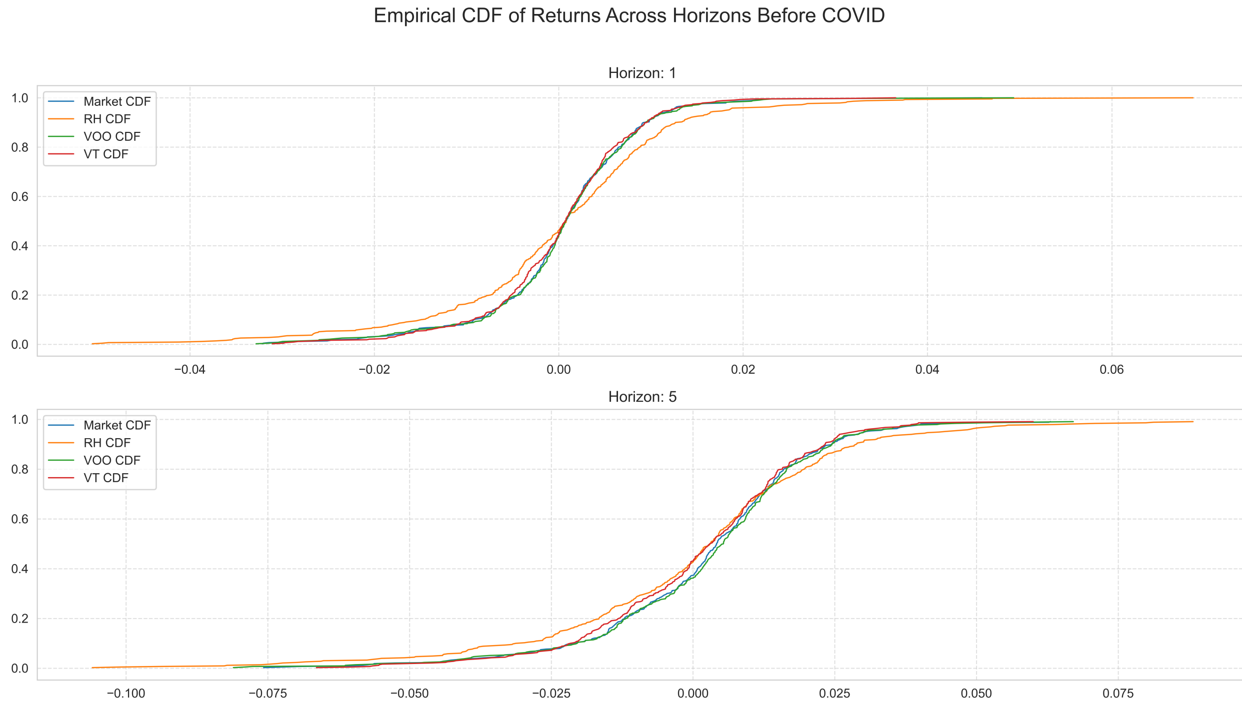
In terms of standard deviation, RH still exhibits more volatility than the market, but the gap is again smaller than the previous data. The 1-day standard deviation for RH is 0.013490, compared to 0.008745 for the market, which shows more volatility for RH but with a smaller gap compared to the earlier dataset where RH had much higher volatility. For the 5-day standard deviation, RH has 0.026549, compared to 0.019395 for the market. The difference is still significant, but once again, smaller than the previous dataset where RH showed greater variability.

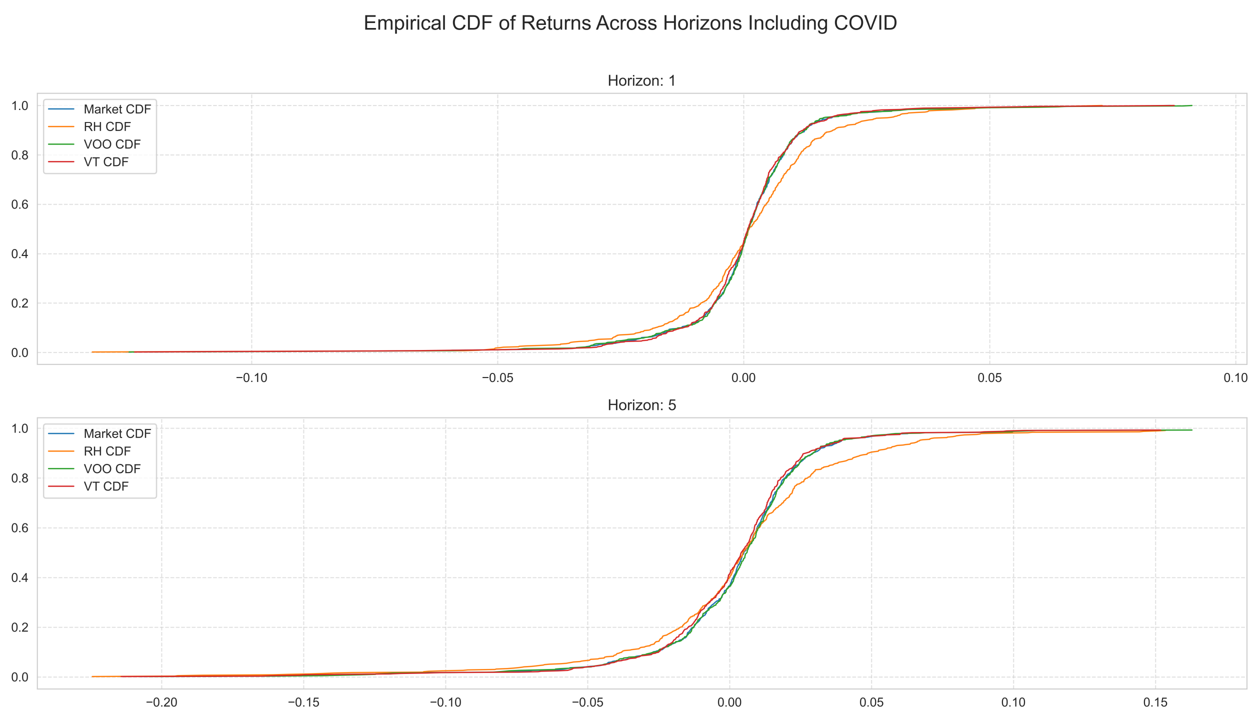
In conclusion, while RH still exhibits more volatility than the market across both horizons, it now shows lower returns than the market for both 1-day and 5-day periods, possibly due to a more consistent left tail. Detailed distribution are in table 3.

Here below the plots of the CDFs and PDFs, both including and exluding covid:


Rolling Market vs Retail Returns Distribution Across Horizons Before COVID
Horizon: 1
Horizon: 5
Density
Market Distribution
RH Distribution
VOO Distribution
VT Distribution


Rolling Market vs Retail Returns Distribution Across Horizons Including COVID
Horizon: 1
Horizon: 5
Density
Market Distribution
RH Distribution
VOO Distribution
VT Distribution




### 3.3.2 Comments

The short-term return distribution for the RH portfolio is noticeably ”flatter” (higher variance/dispersion) compared to broad market benchmarks like VOO or VT. This is consistent with the "buy-the-dip" behavior highlighted by [Fedyk, 2024] and [Ardia et al., 2023]. Actively buying stocks after extreme negative returns means engaging with assets currently experiencing heightened volatility. Even if the average next-day return was positive during the sample period (as Fedyk found for 1-day holds), the range of potential outcomes for these stressed stocks is much wider than for the diversified market, contributing to the fatter tails and lower peak in the distribution.

A primary driver of the flatter distribution is likely the significant lack of diversification among individual Robinhood investors. As noted by [Fedyk, 2024] and [Welch, 2022], the average user held very few stocks ($\sim$ 3)[5]. Individual, concentrated portfolios inherently carry high idiosyncratic risk, leading to much greater return variance compared to diversified market indices represented by VOO/VT.

Stock selection tilts further contribute to the higher volatility. [Welch, 2022] found RH investors favoured high-volume stocks, which could be associated with higher attention and volatility. [Fedyk, 2024] also found no strong evidence of aversion to idiosyncratic volatility. Additionally, [Ardia et al., 2023] noted stronger reactions in specific sectors like energy. These preferences likely result in a basket of holdings that is intrinsically more volatile than the overall market.

[5]They reach this measure by dividing the estimated number of active users mid august 2020 by the number of open positions, (Section 2.4)

# Appendix A Tables

Table 1: Descriptive Statistics for Daily and Rolling Returns

| | **count** | **mean** | **std** | **min** | **25%** | **50%** | **75%** | **max** |
|---|---|---|---|---|---|---|---|---|
| rh_portfolio | 564 | 0.000719 | 0.018809 | -0.132368 | -0.006164 | 0.001141 | 0.009484 | 0.072851 |
| mc | 564 | 0.000396 | 0.015470 | -0.125496 | -0.003944 | 0.001012 | 0.006481 | 0.086673 |
| VOO | 564 | 0.000438 | 0.015806 | -0.124870 | -0.003874 | 0.000942 | 0.006632 | 0.091087 |
| VT | 564 | 0.000184 | 0.015092 | -0.123763 | -0.004568 | 0.000842 | 0.005926 | 0.087470 |
| rh_portfolio_1_return | 564 | 0.000719 | 0.018809 | -0.132368 | -0.006164 | 0.001141 | 0.009484 | 0.072851 |
| mc_1_return | 564 | 0.000396 | 0.015470 | -0.125496 | -0.003944 | 0.001012 | 0.006481 | 0.086673 |
| VOO_1_return | 564 | 0.000438 | 0.015806 | -0.124870 | -0.003874 | 0.000942 | 0.006632 | 0.091087 |
| VT_1_return | 564 | 0.000184 | 0.015092 | -0.123763 | -0.004568 | 0.000842 | 0.005926 | 0.087470 |
| rh_portfolio_5_return | 564 | 0.003309 | 0.041768 | -0.224427 | -0.012162 | 0.004643 | 0.022078 | 0.153755 |
| mc_5_return | 564 | 0.001940 | 0.031094 | -0.207508 | -0.008577 | 0.004961 | 0.016049 | 0.151511 |
| VOO_5_return | 564 | 0.002152 | 0.030933 | -0.204425 | -0.009377 | 0.005838 | 0.016464 | 0.162820 |
| VT_5_return | 564 | 0.000864 | 0.030673 | -0.214262 | -0.010938 | 0.003977 | 0.014857 | 0.151788 |
| rh_portfolio_30_return | 564 | 0.015173 | 0.133421 | -0.482722 | -0.041325 | 0.020205 | 0.051931 | 0.408751 |
| mc_30_return | 564 | 0.009890 | 0.080443 | -0.401515 | -0.015223 | 0.025072 | 0.046527 | 0.246006 |
| VOO_30_return | 564 | 0.011115 | 0.078031 | -0.401950 | -0.011124 | 0.028635 | 0.046654 | 0.252864 |
| VT_30_return | 564 | 0.003681 | 0.079260 | -0.406688 | -0.020644 | 0.018305 | 0.039820 | 0.224464 |
| rh_portfolio_60_return | 564 | 0.010727 | 0.177731 | -0.377518 | -0.066831 | 0.001284 | 0.070271 | 0.641470 |
| mc_60_return | 564 | 0.016554 | 0.099118 | -0.356261 | -0.013618 | 0.029848 | 0.062050 | 0.338109 |
| VOO_60_return | 564 | 0.019496 | 0.095149 | -0.355392 | -0.009450 | 0.033666 | 0.066970 | 0.337947 |
| VT_60_return | 564 | 0.004301 | 0.101282 | -0.385941 | -0.024094 | 0.012486 | 0.057122 | 0.328680 |
| rh_portfolio_120_return | 564 | -0.014462 | 0.114741 | -0.310504 | -0.098157 | -0.014206 | 0.053267 | 0.370780 |
| mc_120_return | 564 | 0.017214 | 0.075478 | -0.307022 | -0.031108 | 0.030972 | 0.070401 | 0.218409 |
| VOO_120_return | 564 | 0.024238 | 0.074347 | -0.302877 | -0.027697 | 0.034991 | 0.076471 | 0.231377 |
| VT_120_return | 564 | -0.006474 | 0.077296 | -0.333294 | -0.056443 | 0.008282 | 0.042280 | 0.186378 |
| rh_portfolio_564_return | 564 | -0.011075 | 0.123340 | -0.382891 | -0.055196 | -0.014086 | 0.045442 | 0.405724 |
| mc_564_return | 564 | 0.071788 | 0.069591 | -0.200798 | 0.033823 | 0.070623 | 0.106613 | 0.224508 |
| VOO_564_return | 564 | 0.094275 | 0.071760 | -0.168586 | 0.051783 | 0.090626 | 0.134336 | 0.251507 |
| VT_564_return | 564 | 0.001882 | 0.063696 | -0.301083 | -0.024162 | 0.014363 | 0.032343 | 0.121970 |

Table 2: Descriptive Statistics for 1-Day and 5-Day Returns, Covering the Whole Period
*Note: Positive returns indicate the percentage of days in which the log returns were greater than zero.*

| | count | mean | std | min | 25% | 50% | 75% | max | positive returns |
|---|---|---|---|---|---|---|---|---|---|
| rh_portfolio_1_return | 564 | 0.000719 | 0.018809 | -0.132368 | -0.006164 | 0.001141 | 0.009484 | 0.072851 | 0.553191 |
| mc_1_return | 564 | 0.000396 | 0.015470 | -0.125496 | -0.003944 | 0.001012 | 0.006481 | 0.086673 | 0.558511 |
| VOO_1_return | 564 | 0.000438 | 0.015806 | -0.124870 | -0.003874 | 0.000942 | 0.006632 | 0.091087 | 0.563830 |
| VT_1_return | 564 | 0.000184 | 0.015092 | -0.123763 | -0.004568 | 0.000842 | 0.005926 | 0.087470 | 0.547872 |
| rh_portfolio_5_return | 560 | 0.003281 | 0.041909 | -0.224427 | -0.012379 | 0.004643 | 0.022098 | 0.153755 | 0.598214 |
| mc_5_return | 560 | 0.001913 | 0.031198 | -0.207508 | -0.008632 | 0.004961 | 0.016300 | 0.151511 | 0.630357 |
| VOO_5_return | 560 | 0.002128 | 0.031036 | -0.204425 | -0.009442 | 0.005838 | 0.016494 | 0.162820 | 0.635714 |
| VT_5_return | 560 | 0.000839 | 0.030779 | -0.214262 | -0.011044 | 0.003977 | 0.014911 | 0.151788 | 0.583929 |

Table 3: Descriptive Statistics for 1-Day and 5-Day Returns, up to February 3rd 2020
*Note: Positive returns indicate the percentage of days in which the log returns were greater than zero.*

| | count | mean | std | min | 25% | 50% | 75% | max | positive returns |
|---|---|---|---|---|---|---|---|---|---|
| rh_portfolio_1_return | 430 | 0.000115 | 0.013490 | -0.050597 | -0.005461 | 0.000809 | 0.007377 | 0.068808 | 0.537209 |
| mc_1_return | 430 | 0.000419 | 0.008745 | -0.032113 | -0.003126 | 0.000804 | 0.005285 | 0.045916 | 0.553488 |
| VOO_1_return | 430 | 0.000485 | 0.008928 | -0.032828 | -0.003066 | 0.000757 | 0.005096 | 0.049350 | 0.558140 |
| VT_1_return | 430 | 0.000198 | 0.008361 | -0.031068 | -0.003794 | 0.000716 | 0.004853 | 0.036545 | 0.546512 |
| rh_portfolio_5_return | 426 | 0.000259 | 0.026549 | -0.105948 | -0.013623 | 0.002922 | 0.014899 | 0.088194 | 0.570423 |
| mc_5_return | 426 | 0.002091 | 0.019395 | -0.075729 | -0.008188 | 0.004110 | 0.014121 | 0.063052 | 0.624413 |
| VOO_5_return | 426 | 0.002442 | 0.019790 | -0.081061 | -0.008308 | 0.004981 | 0.014449 | 0.067072 | 0.636150 |
| VT_5_return | 426 | 0.001031 | 0.018612 | -0.066412 | -0.010824 | 0.002804 | 0.013208 | 0.060003 | 0.565728 |

# Appendix B Handling Missing Data

The original Robinhood dataset contains missing values for 3,331 securities, primarily in the earlier periods. This means that these securities don't have information for a certain date.

To ensure consistency we adopt a similar method as [Fedyk, 2024]. Their Robinhood portfolio is constructed using the available securities on a daily basis, hence securities with missing values are simply not taken into account for the day. Moreover we drop all securities that they have defined as problematic in the appendix.

Since our CRSP dataset is also a bit different from the one they use, we drop entirely securities that have more than one entry per day.

## References

[Ardia et al., 2023] Ardia, D., Aymard, C., and Cenesizoglu, T. (2023). Fast and Furious: A High-Frequency Analysis of Robinhood Users' Trading Behavior. Papers 2307.11012, arXiv.org.

[Fedyk, 2024] Fedyk, V. (2024). This time is different: Investing in the age of robinhood. Working paper, Arizona State University. Version dated November 2024. Check author's website or SSRN for latest version.

[Welch, 2022] Welch, I. (2022). The wisdom of the robinhood crowd. *Journal of Finance*, 77(3):1489–1527.