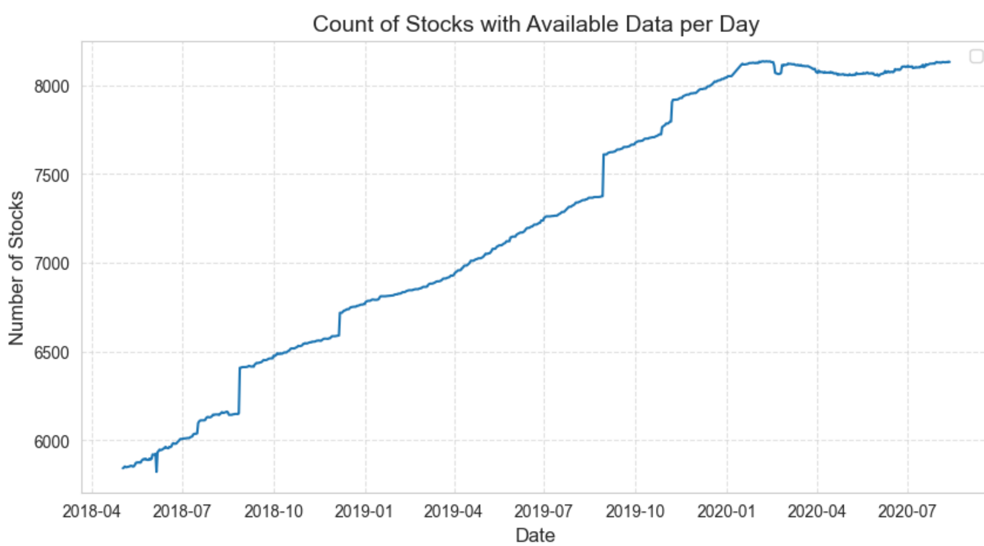
1 Robinhood Dataset

1.1 Description of the Dataset

This data is retrieved from https://robintrack.net/, the creator retrieved data from the official Robinhood API.

The dataset contains the number of Robinhood users holding at least one share of 8,221 securities. The available data spans from February 5, 2018, to August 13, 2020, covering 818 days (data is available also for non-trading days). Although the data was originally recorded hourly, I aggregated it to a daily frequency by computing the average number of holders per day to simplify computations due to the dataset's size. This aggregation can be easily reversed if needed.



Handling NaNs The original dataset contains missing values for 3,331 securities, primarily in the earlier periods. In some cases, assets appear in the dataset only after a certain date, despite being publicly traded before. It is important to distinguish between missing values and zero values, as they represent different concepts. Some securities exhibit a sudden increase from zero to a larger number of holders, but interpreting these as errors would impose an assumption on investor behavior.

Additionally, 1,248 securities have at least one recorded zero in the number of holders. The majority of missing data corresponds to small-cap stocks, which collectively account for at most 3 percent of total market capitalization. Given the limited impact of these securities on overall retail activity, I opted to remove all securities with missing values to ensure consistency in the dataset.

1.1.1 Distribution of Key Features (Log-Transformed)

The distributions of trading volume, market capitalization, and retail holders were initially highly skewed, with a few extreme values dominating the dataset. To address this, I applied a logarithmic transformation: $x' = \log(1 + x)$.

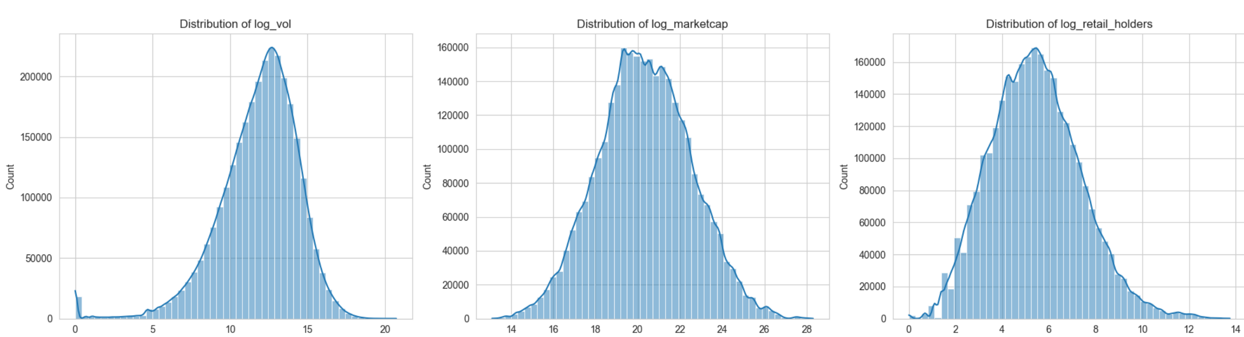
This transformation reduces the impact of outliers, enhances interpretability by making the data more symmetric, and facilitates comparisons between stocks of different sizes.

The key observations after applying the transformation are:

- **Trading Volume:** The distribution appears approximately normal, centered around a peak, with a slight left tail. While most stocks have relatively low trading volume, a few highly traded stocks, such as large-cap or meme stocks, exist but no longer dominate the distribution.

- **Market Capitalization:** The transformed market capitalization data exhibits a bell-shaped curve, suggesting a more balanced spread across small, mid, and large-cap stocks. However, some large-cap stocks remain in the extreme right tail, indicating that a few companies, such as Apple and Microsoft, are significantly larger than the majority.

- **Retail Holders:** The number of retail holders follows a roughly log-normal distribution, confirming that a small number of stocks attract massive retail participation while most remain relatively unpopular. The left tail suggests that many stocks have very few retail holders, reinforcing the notion that retail trading is concentrated in a subset of securities.



1.2 Comparing the Portfolios

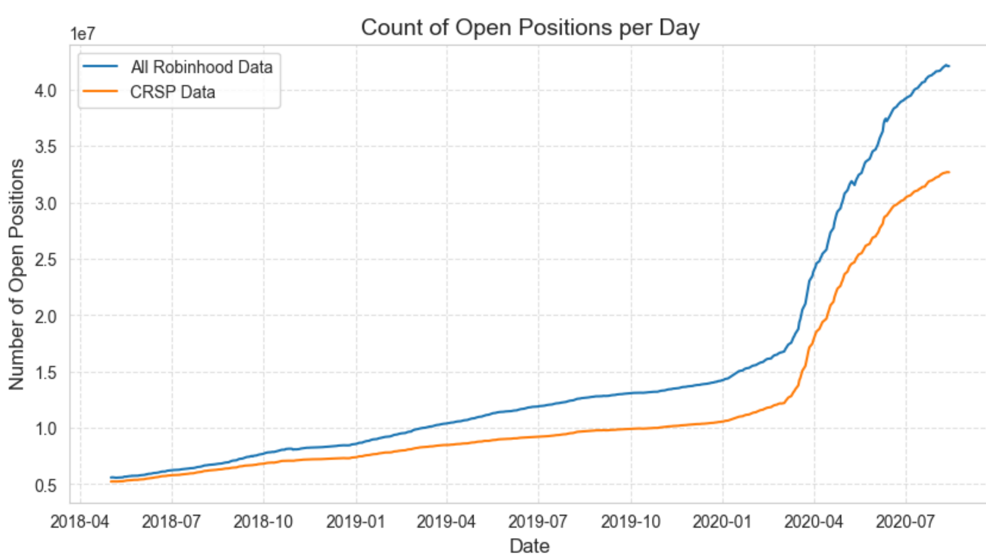
1.2.1 Methodology and Overview

To build a representative portfolio of the average Robinhood investor, it is necessary to retrieve the prices of the securities. A capitalization-weighted approach can be used, multiplying the price of each security by the number of users who hold it. This approach assumes that all Robinhood users hold a similar number of shares for a given ticker, or that the distribution of shares held per user follows a normal distribution.

Over the years covered in the dataset, Robinhood has gained a significant number of users. Data on active users is available on Statista[1], though only on a yearly basis. Comparing the Statista figures with Robinhood's reported numbers for 2023 suggests that the active user count corresponds to December 31 of each year. This data could later be used to normalize the number of users and build a reference portfolio.

The total number of open positions can be computed as the sum of all investors who hold at least one security in each asset, effectively a row-wise sum of the dataset.

Market data for all securities was retrieved from the CRSP[2] database, accessed via WRDS. However, only 8,099 securities are available in CRSP, as it focuses exclusively on American assets. The difference in open positions between the full dataset and the CRSP subset is minimal. If, instead, all securities with missing values are dropped, leaving only 5,221 securities, the gap widens.



[1] https://www.statista.com/statistics/822176/number-of-users-robinhood/

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

The graph illustrates the count of open positions per day on Robinhood from April 2018 to mid-2020, showing a steady increase over time, with a sharp acceleration in early 2020. This surge aligns with the onset of the COVID-19 pandemic, which likely drove a significant influx of new retail investors seeking market opportunities amid economic uncertainty and stimulus checks.

1.2.2 Retail Investors Prefer ”Famous” Stocks

The majority of the securities are common shares, representing about 57.9%. ETFs represent about 23.7% and other funds are the 9.2% of the dataset. Other structured investments, REITs, and ADRs cover the remaining part.

Analysing the securities by market capitalisation about 82.9% is represented by stocks and 9.6% by ETFs. If we look at the ”Retail Market Cap” (i.e. number of positions times price), 89.2% of securities are stocks and 5.8% are ETFs.

Looking at the securities Robinhood users prefer holding, ranked by ”Retail Market Cap”, investors prefer holding smaller cap stock. A qualitative analysis shows ”famous” stocks, such as Tesla, Starbucks, and Nvidia to name a few, to appear among the most popularly owned.

1.2.3 Possible Measures of Divergence

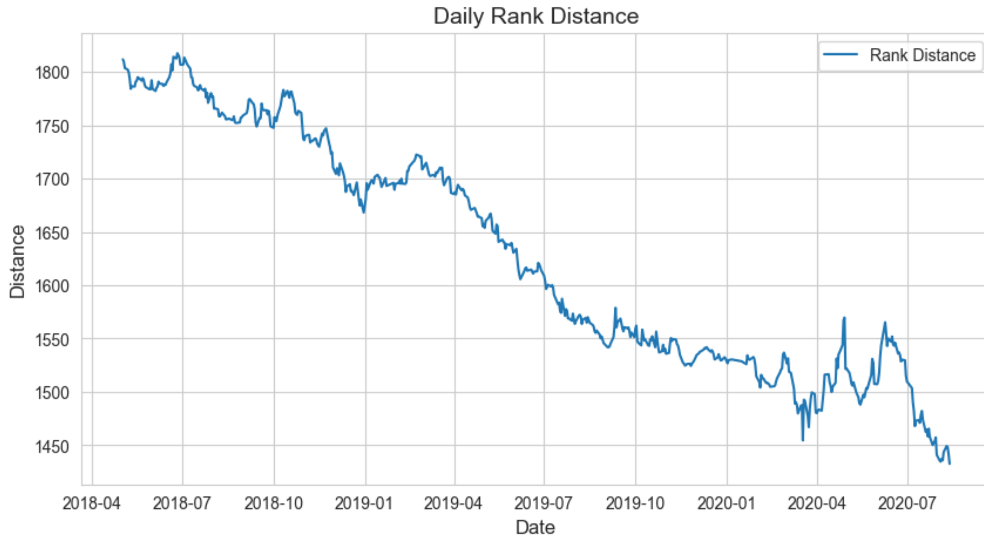
Rank Distance To describe the preference of retail investors for smaller cap stock I propose the following measure:

$$d_R = \sum_{i=1}^{N} \frac{R_i^{\text{Mkt}} - R_i^{\text{RH}}}{R_i^{\text{RH}}}$$

Where R_i^{Mkt} is the rank of the i^{th} security by market cap, and R_i^{RH} is the rank by retail market cap. The normalization by R_i^{RH} reduces the impact of small-cap stocks with minor ranking differences.

The plotted Daily Rank Distance suggests a clear downward trend from early 2018 to mid-2020, indicating that the ranking of stocks by retail market cap has become increasingly aligned with the ranking by total market cap. Initially, the distance is above 1800, gradually declining towards 1450. This implies that retail investors, who originally exhibited a stronger preference for smaller-cap stocks, have progressively shifted towards stocks that are more representative of the broader market.

Between 2018 and 2019, the decline is relatively steady, reflecting a gradual change in retail investment behavior. However, the trend accelerates in 2019 and 2020, suggesting a more



pronounced shift. The beginning of 2020 shows increased volatility, with occasional upward spikes, which could be attributed to market disruptions, possibly linked to the COVID-19 crash and the subsequent retail trading boom. The rapid expansion of retail investing during this period, fueled by stimulus checks and zero-commission trading, may have led to temporary deviations, but the overall trend continues downward.

A sustained decrease in rank distance suggests that retail investors have moved closer to institutional preferences, potentially increasing their exposure to large-cap stocks or index-tracking assets. If this trend persists, it would indicate a continued assimilation of retail behavior into the broader market structure. Conversely, a reversal in this pattern could signal renewed speculative activity or a shift back to small-cap stocks.

2 Analysing Trading Patterns

2.0.1 Presentation of Facts

2.1 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.

A possible solution is building a portfolio in which we assume that all positions hold the same equivalent amount of money in a certain security. This means weighing stocks by their "popularity":

$$Pop_{i,t} = \frac{n_{i,t}}{\sum_i n_{i,t}}$$

where $n_{i,t}$ is the number of users holding a certain stock on a given day. This normalization is necessary to isolate the performance from the large influx of users on the platform.

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

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

In comparison, the value of the reference index is simply the sum of the market cap for each security present in the Robinhood dataset.

2.2 Comparing Returns and Risk measures

Having defined the value for the Robinhood Portfolio and reference index we can analyze their performance, also comparing them to the S&P500 and a world ETF[3] and VT is the ticker of Vanguard Total World Stock ETF) as general market proxies.

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

Keeping this in mind we can obtain the moving average and cumulative returns for all these indices, as well as their distributions.

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.

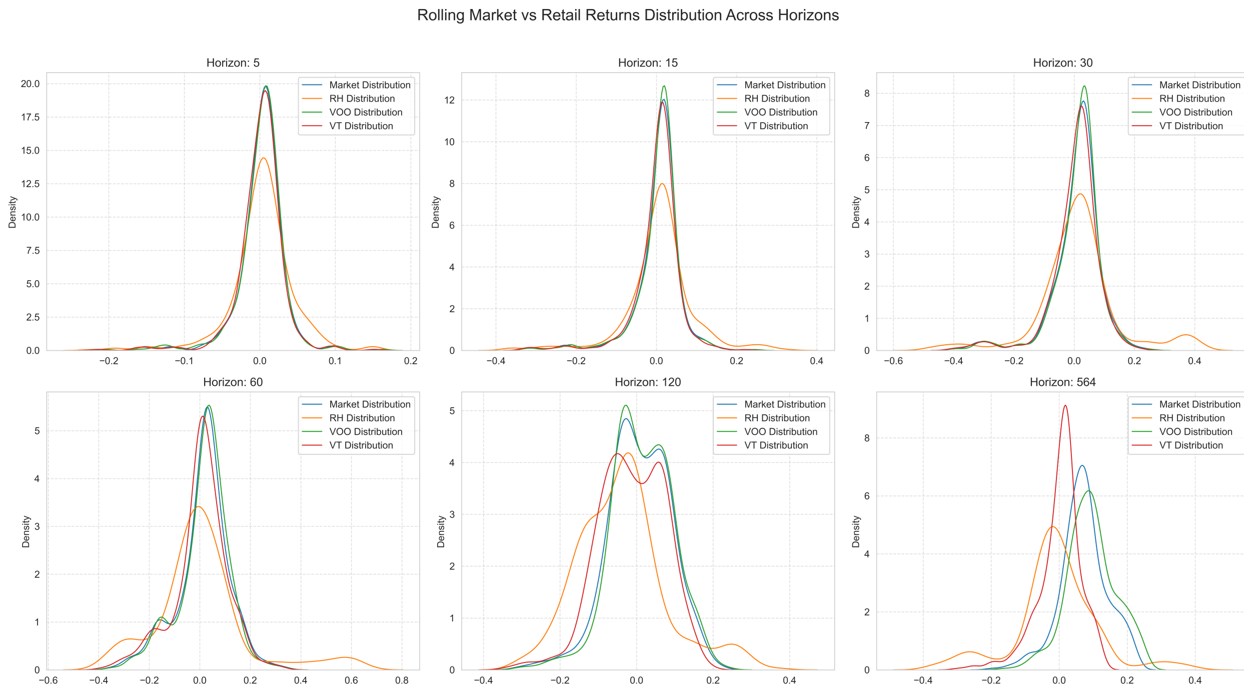
[3] VOO is the ticker of the Vanguard S&P500 ETF

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.

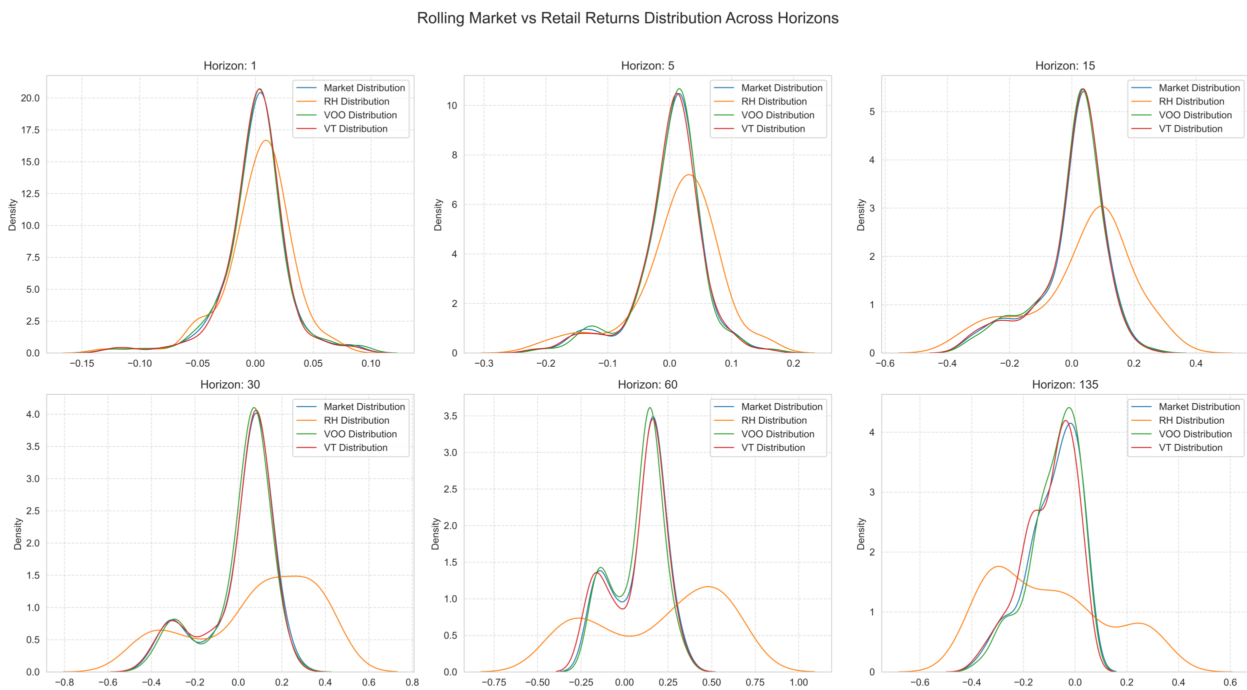
In summary, these distribution plots highlight the increased volatility and higher risk exposure associated with the Robinhood portfolio, especially as the time horizon lengthens. Over both medium and long horizons, retail portfolios are more prone to extreme outcomes, with consistent underperformance 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:



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

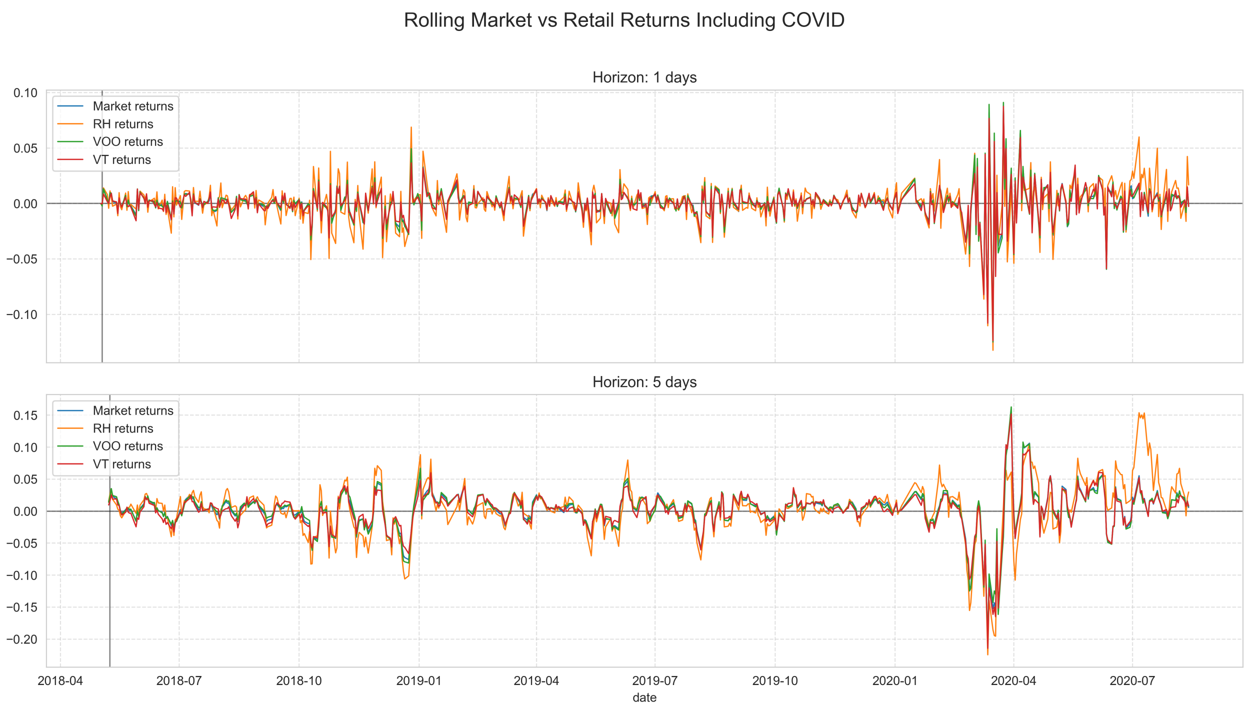
2.3.1 Return Characteristics and Volatility Analysis

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.

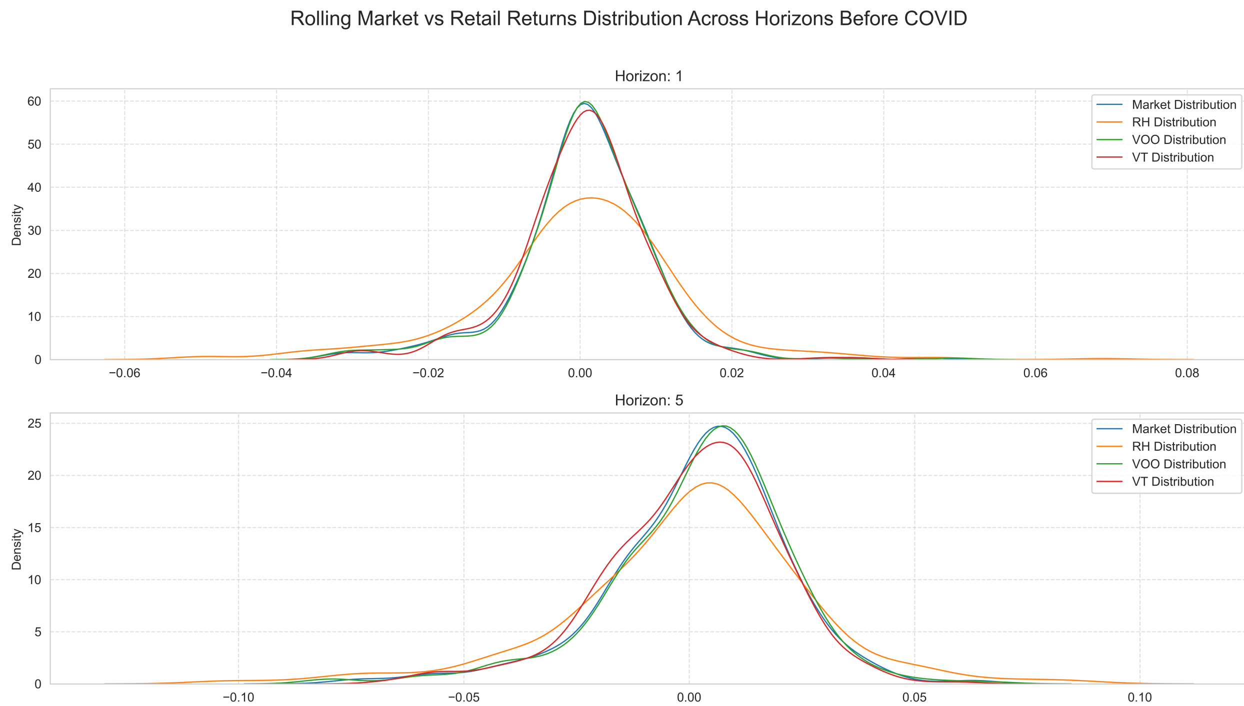
For 1-day returns, RH still has lower average returns compared to the market (MC). RH has an average return of 0.000115, while the market's average is 0.000419.

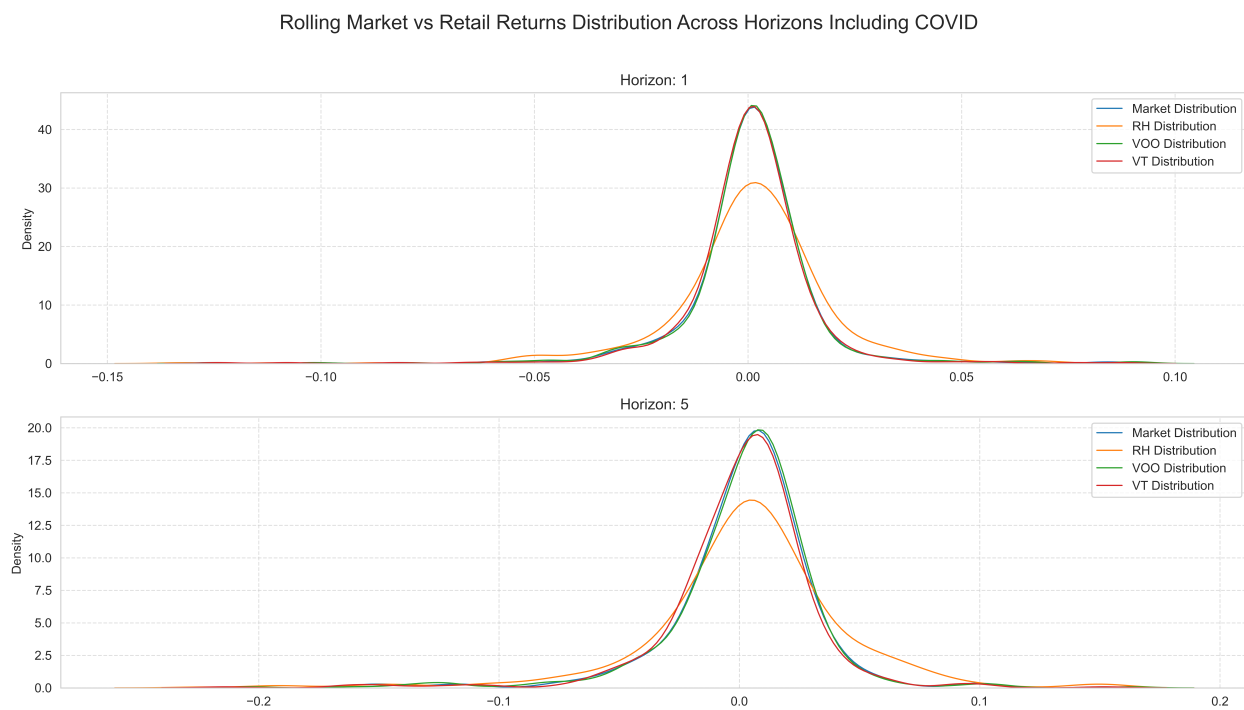
For the 5-day returns, RH's average is much smaller than that of the market. RH has an average return of 0.000259, while the market's average is 0.002091.

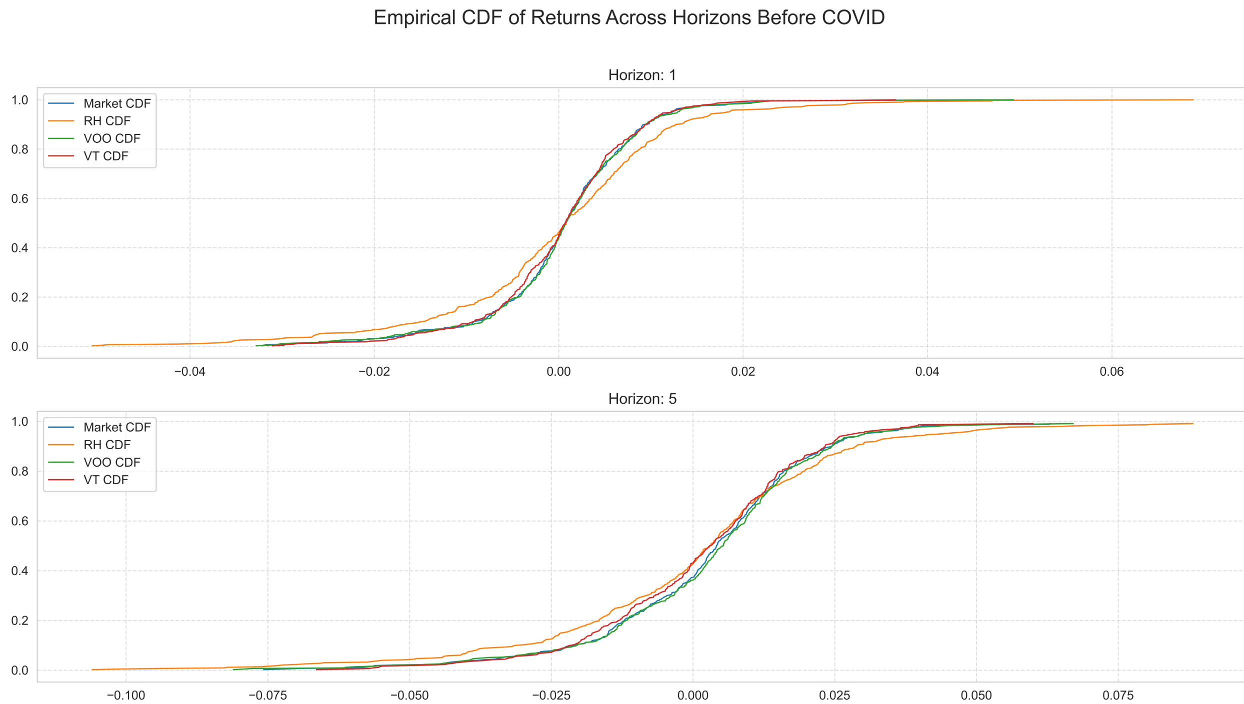
In terms of standard deviation, RH still exhibits more volatility than the market, but the gap is again smaller than the previous data. The 1-day standard deviation for RH is 0.013490, compared to 0.008745 for the market, which shows more volatility for RH but with a smaller gap compared to the earlier 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.

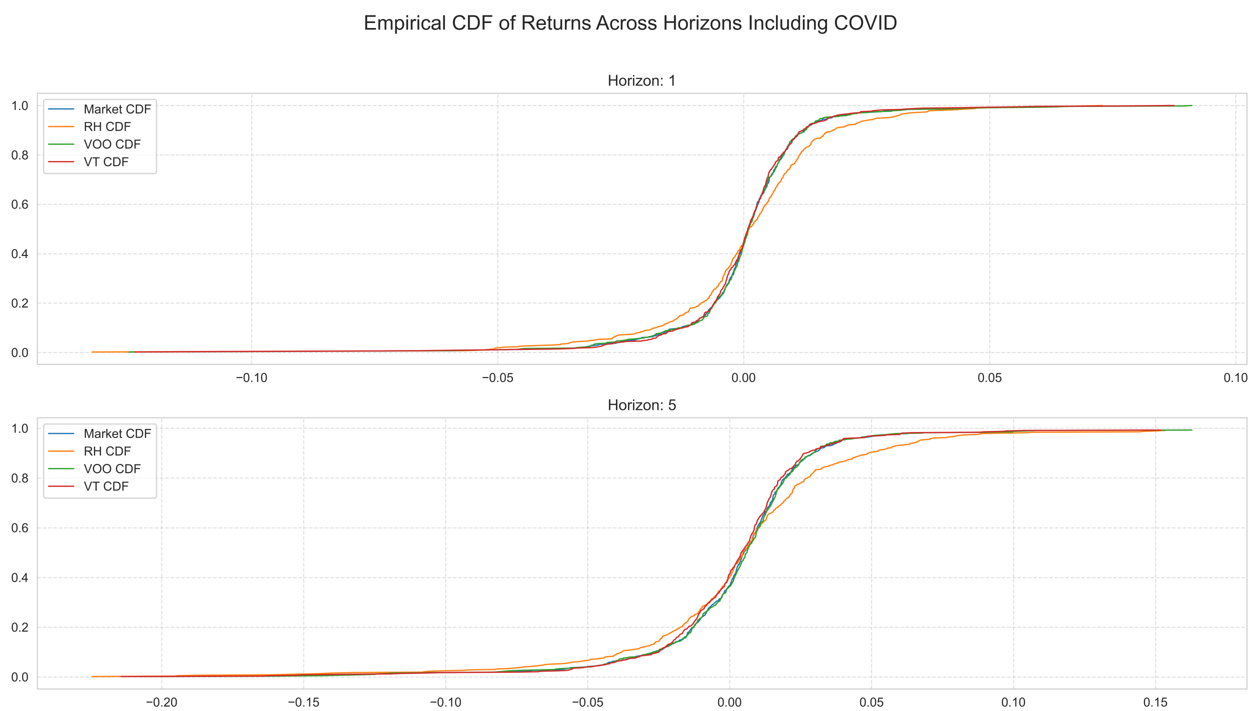
In conclusion, while RH still exhibits more volatility than the market across both horizons, it now shows lower returns than the market for both 1-day and 5-day periods, possibly due to a more consistent left tail. Detailed distribution are in table 3.

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









2.3.2 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)[4]. 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.

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

3 Literature Review

The rise of commission-free trading platforms such as Robinhood has significantly altered the behavior of retail investors, leading to increased speculative trading and attention-driven investment patterns. Existing literature highlights the unique characteristics of these investors, the role of fintech innovations in shaping trading behavior, and the broader market impact of retail-driven trading.

3.1 Retail Investors and Attention-Induced Trading

One of the defining characteristics of Robinhood users is their tendency to engage in attention-induced trading. [Barber and Odean, 2011] document that retail investors are heavily influenced by limited attention and past return performance, often buying stocks that experience large daily price movements. This behavioral bias is further reinforced by Robinhood's design, which prominently features ”Top Movers” lists and real-time price changes [Barber et al., 2021].

Ardia et al. [Ardia et al., 2023] provide a high-frequency analysis of Robinhood traders, showing that they react aggressively within an hour of extreme negative price movements. This suggests that Robinhood users are particularly prone to rapid contrarian trading, potentially due to real-time engagement with financial markets through mobile notifications and social media.

3.2 The Influence of Robinhood on Retail Trading Behavior

The trading behavior of Robinhood users differs from that of traditional retail investors. The simplicity and gamification of the app influence decision-making, leading to increased speculative trading. [Barber et al., 2021] find that Robinhood's ”Top Mover” feature encourages users to buy both extreme gainers and losers at higher rates than traditional retail investors, diverging from the broader retail trading pattern of favoring winners.

Moreover, Robinhood traders exhibit a strong preference for stocks experiencing extreme price movements. [Ardia et al., 2023] report that users react particularly fast to negative price shocks, displaying contrarian tendencies not typically observed in traditional retail trading.

3.3 Market Impact of Robinhood Users

Several studies have examined the broader market impact of Robinhood-driven trading, particularly during periods of heightened retail activity. Concentrated retail buying can lead to short-term price pressure and subsequent reversals. [Barber et al., 2021] show that Robinhood herding episodes-where a large number of users buy the same stock-result in negative abnormal returns of approximately 4.7% over the following 20 days.

Additionally, retail-driven trading was amplified during the COVID-19 pandemic, with a surge in new users engaging in speculative trading. [Ardia et al., 2023] find that Robinhood users intensified their trading activity post-pandemic announcement, particularly in small-cap and volatile stocks.

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

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.

[Barber et al., 2021] Barber, B. M., Huang, X., Odean, T., and Schwarz, C. (2021). Attention induced trading and returns: Evidence from robinhood users. *SSRN Electronic Journal*.

[Barber and Odean, 2011] Barber, B. M. and Odean, T. (2011). The behavior of individual investors. *SSRN Electronic Journal*.

[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.