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 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 Building the Robinhood Portfolio

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

[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.

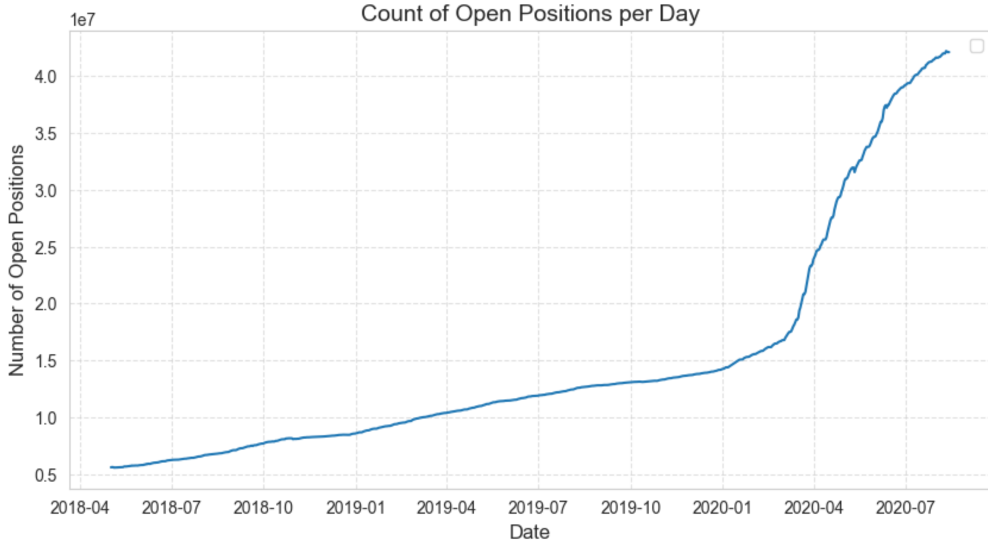

Figure 1: Daily count of open Robinhood positions, April 2018–August 2020.

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 Different Approaches to Compute Performance

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.

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

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. I will call this the "Price" method, or simply my method.

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

$$V_{RH,t} = \sum_{i=1}^{N} w_{i,t}^{\text{dollar}} \cdot P_{i,t} \tag{4}$$

Returns are then computed from the value of the overall portfolio as:

$$r_{RH,t} = \ln\left(\frac{V_{RH,t}}{V_{RH,t-1}}\right) \tag{5}$$

In this paper I prefer using log-returns where possible.

3.1.3 Capturing the Persistence of Investor Composition

Although both approaches ultimately yield a time series of Robinhood portfolio returns, there is a fundamental difference in what these return paths represent.

In the method used by [Fedyk, 2024] and [Welch, 2022], the portfolio is effectively rebalanced every day to reflect the current composition of investor popularity. Each day's return is computed based on that day's weights and the corresponding daily stock-level returns. This provides a valid snapshot of the average return generated by the stocks held on a given day.

However, this approach does not preserve the economic exposure that investors accumulate through time. A stock that was extremely popular for several days but declines in popularity just before a price spike will have minimal influence on the portfolio's return when that spike occurs. Only the weights at time $t-1$ affect the return at time t[5], so the model

[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%

[5] Previous day's weights are taken to prevent look-ahead bias

captures immediate sentiment shifts but not the cumulative effects of holding positions over time.

In contrast, the methodology I propose (5) applies weights to stock prices and computes returns from changes in total portfolio value. This implies that a stock that was heavily weighted yesterday continues to influence portfolio performance today, even if its popularity has declined. The return reflects both the dynamics of price changes and the path dependency of investor composition.

As a result, my method embeds the effects of investor flows, popularity shifts, and concentration in the actual evolution of portfolio value. The cumulative performance is not a sequence of disconnected daily snapshots, but a reflection of how crowd behavior builds, persists, and unwinds over time.

Conceptually, this distinction is important when studying behavioral dynamics. Retail investor behavior—particularly on platforms like Robinhood—is driven not only by cross-sectional preferences at a point in time but also by persistent patterns of attention, sentiment, and herding. A portfolio that evolves with these behavioral shifts provides a more realistic measure of the actual wealth path experienced by retail investors, rather than an idealized, continually rebalanced index.

In this sense, computing returns from the portfolio value offers a more structurally consistent and behaviorally meaningful representation of the Robinhood crowd's investment trajectory.

4 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. Additionally, by recreating their method employed by the other authors we can analyse its return when dealing with all kinds of securities. In section 4.2 I compare returns using only common stocks or the full sample of securities, in the other sections of this paper I will use the full sample unless explicitly stated.

As the other authors have claimed in their papers, the Portfolio built directly from returns had a significantly higher cumulative return compared to the market and positive alpha.

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".

Moreover, [Fedyk, 2024] has analysed extensively the differences between the portfolio obtained using the share method and the dollar method. We'll focus on the dollar method since it is the same approach I use to compute weights.

4.1 Constructing Moving Averages

I begin by computing daily log returns as $r = \ln\left(\frac{P_1}{P_0}\right)$, knowing that for small x, $\ln(1+x) \approx x$. Defining log returns allows us to simply compute moving averages, showing the profitability of the Robinhood portfolio at different time frames. Conceptually, the value of an n-day moving average on a given date T represents the return an investor would have earned by initiating the position at the open of day $T - n$ and holding it continuously up to close of day T. More rigorously, for a given horizon of n days:

$$r_n = \sum_{t=T-n+1}^{T} r_t \approx \ln\left(\prod_{t=T-n+1}^{T} (1 + R_t)\right) \tag{6}$$

where r_t are dauly log returns and R_t are daily percentage returns.

4.2 Retail Performance Under Different Samples

4.2.1 Rolling Returns Across Investment Horizons

Common Stocks Only At short horizons (5–30 days), the two Robinhood portfolios (Fedyk and Mine) display highly similar dynamics, with both closely tracking market indices and exhibiting bursts of volatility during periods of market stress, particularly around the onset of the COVID-19 crash. This suggests that in the very short term, retail investors tend to move in tandem with broader market trends, with limited divergence in return profiles across methodologies. However, at the 120-day horizon, both Robinhood portfolios outperform the S&P 500 and a World ETF[6].

This finding is consistent with the idea that many retail investors, especially on Robinhood, engaged in "buy-the-dip" behavior during the COVID-19 crash. Their increased exposure to beaten-down or speculative stocks during the downturn appears to have been rewarded in the subsequent rebound. Importantly, this also coincides with a period of explosive growth for the platform itself, which may have amplified attention and capital inflows into popular names.

[6] I've used Vanguard's VOO for the S&P500 and Vanguard's VT as a World Equity ETF

Nonetheless, this post-crash outperformance comes after a prolonged period of clear underperformance. Prior to March 2020, both Robinhood portfolios consistently lag behind the benchmark indices, with my method in particular reflecting substantial drawdowns and poor stock selection.

What differentiates the two methods most clearly is the strength of the post-COVID recovery. While Fedyk's method shows a relatively steady climb, my price-based approach rebounds even more sharply after March 2020. This reflects the fact that, under my methodology, investor positions are not rebalanced away from prior favorites. As a result, stocks that surged after the crash contributed disproportionately to the portfolio's recovery.

In sum, the 120-day results provide two key insights: first, that retail traders on Robinhood did benefit from post-crisis market dynamics, and second, that the magnitude and nature of this benefit depends heavily on the modeling approach, particularly when capturing persistence in portfolio composition.

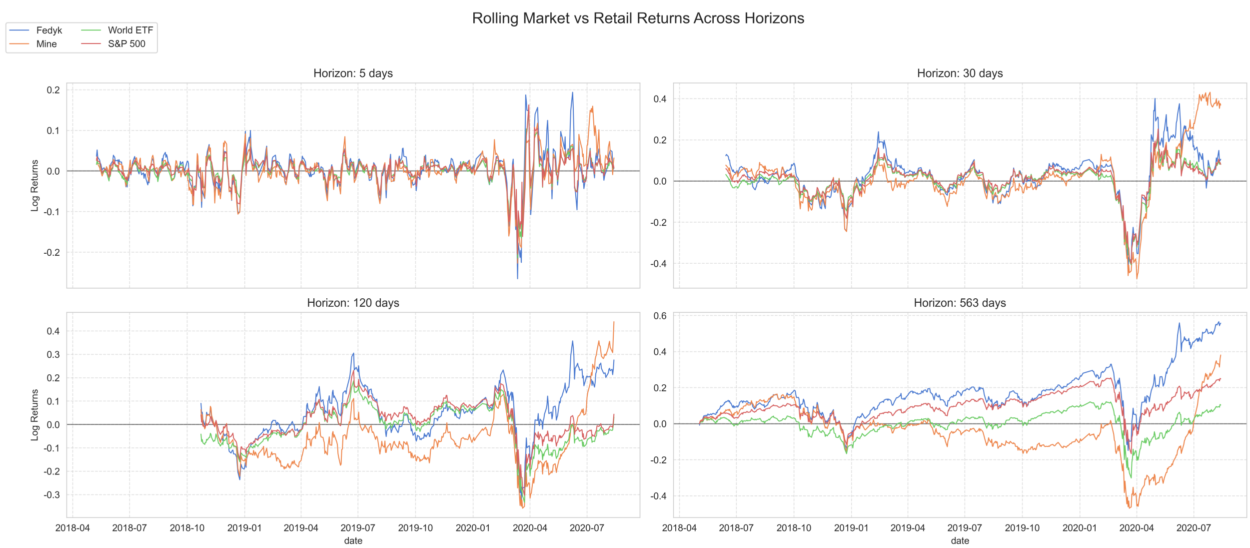

Figure 2: Rolling log-returns of Robinhood and market portfolios at four investment horizons (stock-only sample)

Full Universe of Securities We now extend the analysis to all securities in the dataset, including ETFs, REITs, and structured products.

Expanding the sample, we still observe that short-term movements (5–30 days) remain closely correlated across all portfolios, with limited divergence in returns or volatility between methods.

However, the performance gap widens at longer horizons. In contrast to the stock-only case, where both Robinhood portfolios outperform after the crash, here the drawdowns, particularly in the price-based portfolio, are deeper and more persistent.

Low performance spans the entire pre-COVID period: my portfolio underperforms continuously throughout 2019, while Fedyk's stays closer to the benchmarks but still lags in absolute terms.

At the 563-day horizon, both Robinhood portfolios end below the S&P 500 and the World ETF. My portfolio, while showing a stronger post-crash rebound, barely catches up to the S&P 500 by the end of the sample, and only due to its heavier exposure to post-crash winners. Fedyk's method performs slightly better but remains clearly below the benchmark, reversing the apparent outperformance seen in the stock-only sample.

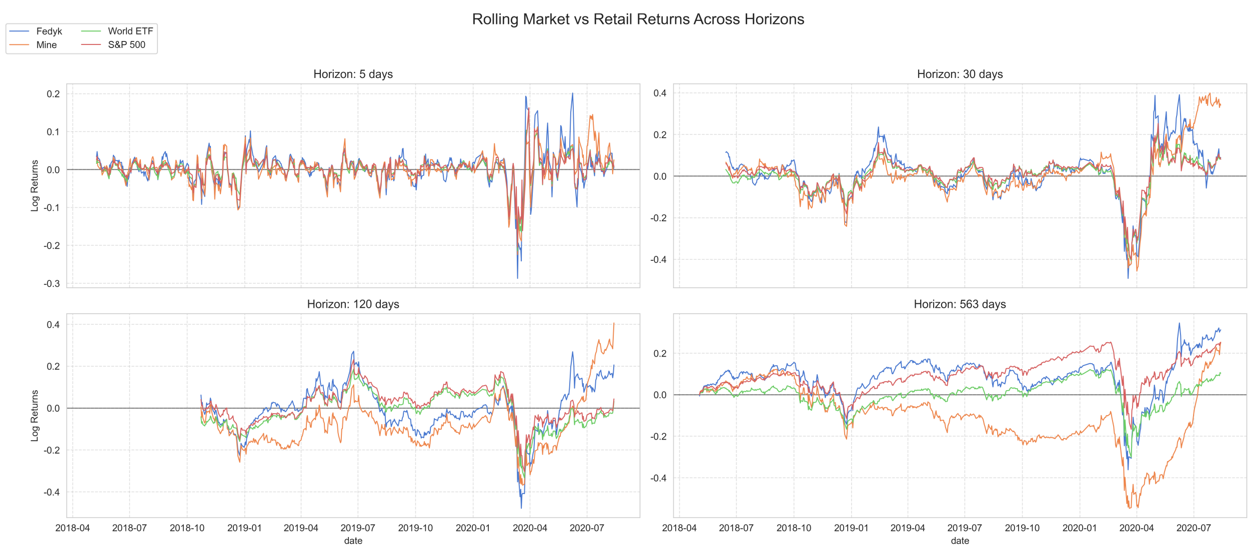

Figure 3: Rolling log-returns of Robinhood and market portfolios at four investment horizons (complete sample)

A detailed description of the distributions can be found in table 2.

4.2.2 Distribuional insights

Common Stocks Only The distribution of returns across horizons provides further evidence on the differences between the Robinhood portfolios and the benchmarks.

At short horizons (5–30 days), all portfolios are tightly centered around zero, with relatively similar dispersion. Both Robinhood portfolios display slightly higher volatility than the S&P 500 and the World ETF, with standard deviations of approximately 0.045 for five-day returns, compared to about 0.03 for the benchmarks. However, mean returns remain close to zero for all portfolios, and short-term behavior shows limited divergence across methods.

At the 120-day horizon, differences become more evident. While Fedyk's portfolio maintains a positive mean log return of approximately 0.05, my price-based portfolio exhibits a negative mean return of about -0.06. The median is also much worse, at about -0.14 versus -0.02. This shift is reflected in the distribution shapes, with my portfolio showing a wider left tail and greater dispersion relative to both Fedyk's method and the benchmarks.

At the 563-day horizon, the gap further widens. The price-based portfolio remains centered around negative returns, with a mean log return of approximately -0.04, while the rebalanced portfolio achieves a positive mean return of 0.17. In contrast, the S&P 500 maintains a strong positive outcome, with a mean log return close to 0.1.

Despite the strong rebound observed after the COVID-19 crash, the cumulative performance of the price-based portfolio remains significantly weaker, often with higher standard deviation.

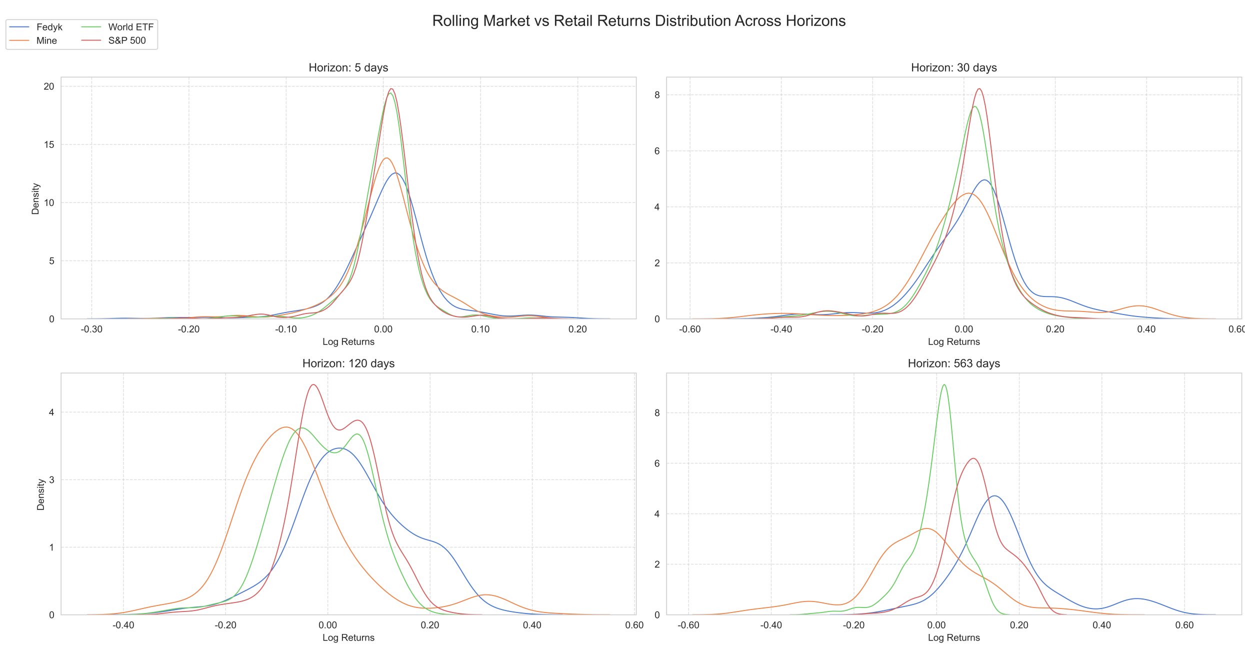

Figure 4: Distribution of rolling log-returns for retail and benchmark portfolios across investment horizons (stock-only sample)

A detailed description of the distributions can be found in table 1.

Full Universe of Securities Expanding the analysis to include all types of securities slightly alters the distributional patterns compared to the stock-only case.

At short horizons (5–30 days), return distributions remain centered around zero and maintain a similar dispersion across all portfolios. Standard deviations are comparable to the stock-only case, around 0.02 for both Robinhood portfolios at the daily level and 0.04 for five-day returns. Mean returns are very close to zero, confirming that short-term dynamics are largely unaffected by the broader sample.

At the 120-day horizon, however, differences become more evident. Both Robinhood portfolios exhibit flatter distributions with thicker left tails compared to the benchmarks. In particular, my price-based portfolio records a negative mean log return of approximately -0.07, while Fedyk's method also turns slightly negative at around -0.004, unlike in the stock-only case where it remained positive. The S&P 500 maintains a positive mean return over the same horizon, reinforcing the relative weakness of retail portfolios when more asset types are included.

At the cumulative horizon, the gap becomes substantial. My portfolio shows a strongly left-skewed distribution with a mean log return of approximately -0.10. Fedyk's portfolio, although positive at around 0.087, remains below the S&P 500, which achieves a mean return close to 0.1. The World ETF again displays lower returns, in line with its broader exposure to international markets.

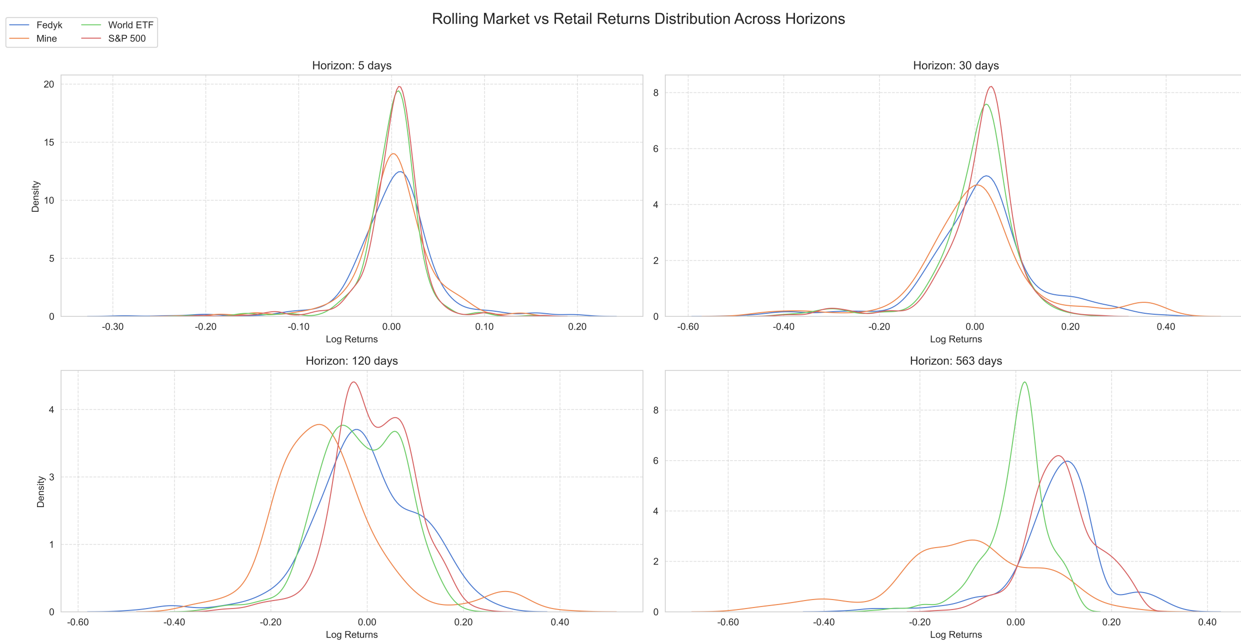

Figure 5: Distribution of rolling log-returns for retail and benchmark portfolios across investment horizons (complete sample)

Descriptive statistics supporting these findings are reported in Table 2.

4.3 Analysis of Short-Term Returns and the Impact of COVID

Comparing the daily returns for the whole period available we can already observe distinct behavior in terms of returns and distributions for the market and Robinhood indeces. To test whether there are statistically significant differences beteen the mean daily returns of the Robinhood portfolios, the S&P 500 and the world ETF, I conduct an ANOVA test. The null hypothesis is that all portfolios have equal mean daily returns.

4.3.1 Covering the Whole Period

As expected from the results regarding the cumulative returns, mean daily returns are very similar for the Robinhood Portfolios. Fedyk's method has a mean of 0.000555, while the method based on prices has a mean of 0.000450. The ANOVA analysis conducted on these two portfolios, equal to a t-test in this case, has a p-value of 0.9273. This suggests that at the daily frequency the expected growth rate, i.e. the mean log returns, of the Robinhood portfolios are not statistically different.

In terms of standard deviation, the Robinhood portfolios have relatively larger values, around 0.02, while the market indeces hvae values around 0.15. This is consistent with what can be seen from the distributions: retail portfolios have fatter tails while modal returns appear similar across all timeseries.

Conducting ANOVA tests on all possible combinations of these four timeseries, none has an acceptable p-value, results are in table 4. However, conducting a Fligner test to assess difference in variances, the Robinhood portfolios show statistically significant differet variances than the market proxies, results are in table 6.

Here below the plots of the distributions, while the returns are in table 2:

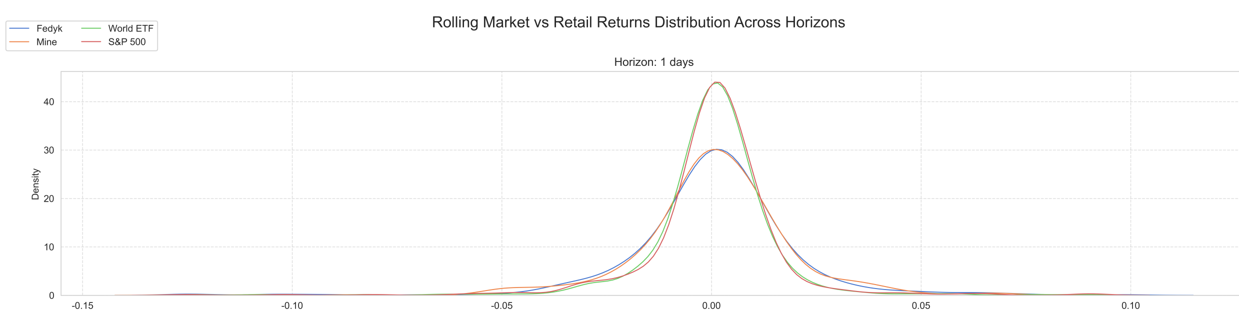

Figure 6: Distribution of daily log-returns for retail and benchmark portfolios (complete sample)

4.3.2 Excluding COVID

This results on daily returns, however, are probably impacted by the noise of the March 2020 crash. I run the same analysis filtering the dataframe up to February 3rd 2020, the date in which the pandemic was declared in the US.

In this case point estimates for means differ greatly even among Robinhood Portfolios, with the price based approach yielding -0.000328 on average versus Fedyk's 0.000246. Nonetheless, also at this level returns are not statistically significant, results can be found in table 5.

In terms of standard deviation, the market indices show again clearly a different distribution, with variances being markably lower. This is corroborated by fligner tests, available in table 7.

Here below the plots of the distributions, while the returns are in table 3:

Figure 7: Distribution of daily log-returns for retail and benchmark portfolios (complete sample, excluding COVID)

4.4 Comments

Daily returns show a deceptively optimistic view, with the different series having statistically equal log-returns. However, the retail portfolios carry systematically higher day-to-day risk, amd this compounds as underperformance at the cumulative level before the pandemic.

A one-way ANOVA on daily log returns fails to reject equality of means for any group of series, both including and excluding the pandemic.

However, looking at the risk dimension, stand deviations differ sharply. Fligner-Killeen tests reject homogeneity at any α level whenever a retail series is compared with a market proxy. As highlighted earlier, this can be easily seen from the shape of the distributions, with correspondingly fatter tails. In log space, larger dispersion automatically lowers longrun growth because every large swing pulls the cumulative sum away from the average trend. In other words, retail investors accept more noise than the market but earn no meaurable extra drift in a single day.

Although ANOVA cannot reject equality between the Robinhood portfolios, the point estimates themselves are not identical (compare table 3). The gap in their mean returns, about -0.0006 log points, rapidly cumulates to -0.25 log points. The test lacks power because daily @s is large; the economic impact measured in compounding is evident.

Path dependence widens the difference. The price-weighted series 5 embeds a negative correlation between returns and remaining capital. When a stock falls, its contribution to the portfolio value shrinks, and therefore any subsequent rebound is applied to less capital, exactly how a normal portfolio would work. The return-weighted construction re-anchors weights every market close and therefore avoids this drag. Losses in early 2019 thus penalise the price-weighted portfolio twice.

5 Assessing Risk Preferences: A Dual-Criterion Approach

5.1 Setup and Definitions

The results of section 4 paint very different pictures of retail investors. Using the method set forth by [Welch, 2022] and [Fedyk, 2024], analysed also in section 4.2.1, yields superior returns and similar drawdowns to the market. They also conclude that the Robinhood crowd has achieved positve alpha when analysed under different factor models (table VII, IX, X in [Welch, 2022] and table 16 in [Fedyk, 2024]). These results appear to be in contrast with the existing literature on the retail investing, most notably [Barber and Odean, 2000].

A more fundamental question, however, is whether those returns are attractive once investors' attitudes toward risk are taken into account. This section evaluates the Robinhood portfolio against its market benchmarks using two complementary criteria.

First, I adopt the constant-relative-risk-aversion (CRRA) framework, in line with the majority of asset pricing work.

$$U(W) = \begin{cases} \frac{W^{1-\gamma}-1}{1-\gamma}, \gamma \neq 1 \\ \ln(W), \gamma = 1 \end{cases} \tag{7}$$

By computing expected utility of both the Robinhood and benchmark portfolios over a grid of possible risk aversion (γ) values, I identify the cutoff γ^* such that a representative

CRRA investor is indifferent between the two, formally:

$$\gamma^* = \min \{\gamma_j : \mathbb{E}[U_p(\gamma_j)] \geq \mathbb{E}[U_m(\gamma_j)]\} \tag{8}$$

This delivers a concise, parametric summary of how risk preferences may shape portfolio choice.

However, this method cannot deliver precise estimates given the limited sample size. I therefore employ another method to directly estimate the risk aversion γ following the Generalized Method of Moments (GMM) framework introduced by [Hansen and Singleton, 1982].

$$\mathbb{E}\left[\beta \frac{U'(c_{t+1})}{U'(c_t)} R_{t+1} - 1\right] = 0 \tag{9}$$

where R_{t+1} is the realized return on the asset at time $t+1$.

Rewriting equation 9 and assuming CRRA utility we arrive at the following condition:

$$\mathbb{E}\left[\beta \left(\frac{c_{t+1}}{c_t}\right)^{-\gamma} R_{t+1} - 1\right] = 0 \tag{10}$$

Then, using portfolio returns as a proxy of consumption and letting $\beta = \frac{1}{1+\bar{r_f}}$ we derive the following GMM moment condition:

$$g(\gamma) = \mathbb{E}\left[\frac{R_{t+1}^{-\gamma}}{1+\bar{r}_f} R_{t+1} - 1\right] = 0 \tag{11}$$

I then use a root-solving algorithm to find the γ that satisfies equation 11.

Second, I apply first- and second-order stochastic dominance tests (FSD and SSD) to the same return distributions. This allows to avoid unnecesary, though conventional, assumptions regarding functional forms or parameterisation. Log-Normality might well not be respected for different distributions, stochastic dominance tests take into account the shape of empirical CDFs to answer stronger questions.

5.2 Expected Utility and Cutoff

As birefly explained above, although equation 8 delivers a concise summary for what paramaters of risk aversion a rational utility-maximizer agent with CRRA utility would choose the Robinhood portfolio, the limited size and noise of the sample imply wide conference intervals for the estimated expected utilities. In practice, this remains a useful conceptual framework to understand how risk preference and believes may affect portfolio choice, but in limited samples its numerical outputs are more illustrative than definitive.

Appendix A Tables

Table 1: Descriptive Statistics for Daily and Rolling Returns
Note: Returns accounting only for investments in Stocks.

	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
Fedyk daily return	563	0.000990	0.019894	-0.135995	-0.005807	0.001516	0.009167	0.105441
Mine daily return	563	0.000677	0.019209	-0.125590	-0.006681	0.001363	0.009784	0.071628
VT daily return	563	0.000185	0.015106	-0.123763	-0.004592	0.000886	0.005933	0.087470
VOO daily return	563	0.000443	0.015820	-0.124870	-0.003893	0.000976	0.006653	0.091087
Fedyk 5 return	559	0.004866	0.046404	-0.265341	-0.015031	0.007872	0.025282	0.193965
Mine 5 return	559	0.002979	0.043110	-0.226991	-0.013770	0.003621	0.021740	0.159707
VT 5 return	559	0.000824	0.030805	-0.214262	-0.011045	0.003956	0.014927	0.151788
VOO 5 return	559	0.002111	0.031063	-0.204425	-0.009442	0.005716	0.016506	0.162820
Fedyk 30 return	534	0.025268	0.114955	-0.431533	-0.032448	0.035874	0.072017	0.401292
Mine 30 return	534	0.012159	0.140314	-0.474366	-0.051104	0.009054	0.054639	0.431367
VT 30 return	534	0.002735	0.081324	-0.406688	-0.024941	0.017664	0.041113	0.224464
VOO 30 return	534	0.009843	0.079924	-0.401950	-0.015450	0.027341	0.046977	0.252864
Fedyk 120 return	444	0.050804	0.114293	-0.330870	-0.021276	0.046242	0.130711	0.357556
Mine 120 return	444	-0.059004	0.127178	-0.358205	-0.139490	-0.074974	-0.015135	0.439583
VT 120 return	444	-0.012628	0.085645	-0.333294	-0.070621	-0.012804	0.059034	0.186378
VOO 120 return	444	0.013786	0.079450	-0.302877	-0.037033	0.011899	0.073431	0.231377
Fedyk 563 return	563	0.168894	0.129435	-0.148334	0.100301	0.146221	0.199060	0.565657
Mine 563 return	563	-0.038567	0.143947	-0.468443	-0.114762	-0.027966	0.041386	0.380918
VT 563 return	563	0.002293	0.063753	-0.300675	-0.023998	0.014837	0.032750	0.122378
VOO 563 return	563	0.096803	0.071714	-0.166225	0.054575	0.093080	0.136742	0.253868

Table 2: Descriptive Statistics for Daily and Rolling Returns
Note: Returns accounting for investments in all types of securities. ETF returns are identical to table 1.

	count	mean	std	min	25%	50%	75%	max
Fedyk daily returns	563	0.000555	0.020000	-0.125369	-0.006658	0.000754	0.008755	0.097995
Mine daily returns	563	0.000450	0.018710	-0.126475	-0.006472	0.000606	0.009044	0.072808
VT daily return	563	0.000185	0.015106	-0.123763	-0.004592	0.000886	0.005933	0.087470
VOO daily return	563	0.000443	0.015820	-0.124870	-0.003893	0.000976	0.006653	0.091087
Fedyk 5 return	559	0.002684	0.047496	-0.287100	-0.017592	0.005106	0.022556	0.201768
Mine 5 return	559	0.001891	0.041707	-0.224346	-0.015152	0.002165	0.020423	0.145245
VT 5 return	559	0.000824	0.030805	-0.214262	-0.011045	0.003956	0.014927	0.151788
VOO 5 return	559	0.002111	0.031063	-0.204425	-0.009442	0.005716	0.016506	0.162820
Fedyk 30 return	534	0.012231	0.118341	-0.491574	-0.044795	0.018809	0.055543	0.391200
Mine 30 return	534	0.005924	0.134409	-0.456420	-0.056865	0.006054	0.044482	0.399350
VT 30 return	534	0.002735	0.081324	-0.406688	-0.024941	0.017664	0.041113	0.224464
VOO 30 return	534	0.009843	0.079924	-0.401950	-0.015450	0.027341	0.046977	0.252864
Fedyk 120 return	444	-0.004432	0.114878	-0.478685	-0.062876	-0.010586	0.076930	0.271451
Mine 120 return	444	-0.076568	0.124668	-0.368195	-0.159984	-0.095393	-0.037126	0.406700
VT 120 return	444	-0.012628	0.085645	-0.333294	-0.070621	-0.012804	0.059034	0.186378
VOO 120 return	444	0.013786	0.079450	-0.302877	-0.037033	0.011899	0.073431	0.231377
Fedyk 563 return	563	0.086945	0.096844	-0.361597	0.050499	0.096675	0.134919	0.345822
Mine 563 return	563	-0.103880	0.152561	-0.547158	-0.193259	-0.096858	0.008830	0.253266
VT 563 return	563	0.002293	0.063753	-0.300675	-0.023998	0.014837	0.032750	0.122378
VOO 563 return	563	0.096803	0.071714	-0.166225	0.054575	0.093080	0.136742	0.253868

Table 3: Descriptive Statistics for Daily Returns, up to February 3rd 2020.
Note: Returns accounting for investments in all types of securities.

	count	mean	std	min	25%	50%	75%	max
Mine	429	-0.000328	0.013581	-0.049700	-0.006121	-0.000106	0.007070	0.065745
Fedyk	429	0.000246	0.012218	-0.047821	-0.005735	0.000549	0.007639	0.052644
VT	429	0.000200	0.008370	-0.031068	-0.003812	0.000766	0.004879	0.036545
VOO	429	0.000492	0.008938	-0.032828	-0.003072	0.000783	0.005103	0.049350

Table 4: Results for One-Way ANOVA Tests on Daily Returns
This results cover the whole period.

subset	F Statistic	p-value
(Fedyk, VT)	0.123106	0.725755
(VOO, VT)	0.078475	0.779426
(Mine, VT)	0.068498	0.793584
(Fedyk, VOO)	0.010935	0.916736
(Fedyk, Mine)	0.008335	0.927275
(Fedyk, VOO, VT)	0.069435	0.932923
(Fedyk, Mine, VT)	0.062966	0.938977
(Mine, VOO, VT)	0.046579	0.954490
(Fedyk, Mine, VOO, VT)	0.045550	0.987099
(Fedyk, Mine, VOO)	0.006693	0.993330
(Mine, VOO)	0.000046	0.994589

Table 5: Results for One-Way ANOVA Tests on Daily Returns, up to February 3rd 2020

subset	F Statistic	p-value
(Mine, VOO)	0.861444	0.353597
(Fedyk, Mine)	0.398907	0.527823
(Mine, VT)	0.321035	0.571135
(Mine, VOO, VT)	0.517251	0.596281
(VOO, VT)	0.243873	0.621550
(Fedyk, Mine, VOO)	0.451564	0.636733
(Fedyk, Mine, VT)	0.273712	0.760596
(Fedyk, Mine, VOO, VT)	0.343216	0.794081
(Fedyk, VOO)	0.055235	0.814249
(Fedyk, VT)	0.028370	0.866282
(Fedyk, VOO, VT)	0.092718	0.911456

Table 6: Results for Fligner Tests on Daily Returns

Results cover the whole period.

subset	F Statistic	p-value
(Fedyk, Mine, VOO, VT)	73.410013	0.000000
(Mine, VOO, VT)	52.796594	0.000000
(Fedyk, VOO, VT)	49.720452	0.000000
(Fedyk, Mine, VT)	47.695216	0.000000
(Fedyk, Mine, VOO)	46.156948	0.000000
(Mine, VT)	38.480331	0.000000
(Mine, VOO)	37.127424	0.000000
(Fedyk, VT)	36.387775	0.000000
(Fedyk, VOO)	34.874042	0.000000
(Fedyk, Mine)	0.031996	0.858037
(VOO, VT)	0.003157	0.955192

Table 7: Results for Fligner Tests on Daily Returns, , up to February 3rd 2020

subset	F Statistic	p-value
(Fedyk, Mine, VOO, VT)	83.536860	0.000000
(Mine, VOO, VT)	64.187897	0.000000
(Fedyk, VOO, VT)	54.358126	0.000000
(Fedyk, Mine, VT)	53.377374	0.000000
(Fedyk, Mine, VOO)	51.856316	0.000000
(Mine, VT)	45.431002	0.000000
(Mine, VOO)	43.773368	0.000000
(Fedyk, VT)	39.157744	0.000000
(Fedyk, VOO)	37.465317	0.000000
(Fedyk, Mine)	0.576961	0.447506
(VOO, VT)	0.002907	0.957003

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

[Barber and Odean, 2000] Barber, B. M. and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, 55(2):773–806.

[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.

[Hansen and Singleton, 1982] Hansen, L. P. and Singleton, K. J. (1982). Generalized instrumental variables estimation of nonlinear rational expectations models. *Econometrica*, 50(5):1269–1286.

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