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Linking Social and Wealth Metrics to Portfolio Outcomes in DeFi: A Statistical Analysis of On-Chain Portfolio Data

Tom Celig
University of Cologne, celig@wim.uni-koeln.de

Lazar Milosevic
University of Cologne, milosevic@wim.uni-koeln.de

Tim Alvaro Ockenga
University of Cologne, ockenga@wim.uni-koeln.de

Detlef Schoder
University of Cologne, schoder@wim.uni-koeln.de

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Tom Celig
Cologne Institute for Information Systems, University of Cologne
Pohligstraße 1, 50969 Cologne
celig@wim.uni-koeln.de

Lazar Milosevic
Cologne Institute for Information Systems, University of Cologne
Pohligstraße 1, 50969 Cologne
milosevic@wim.uni-koeln.de

Tim Alvaro Ockenga
Cologne Institute for Information Systems, University of Cologne
Pohligstraße 1, 50969 Cologne
ockenga@wim.uni-koeln.de

Detlef Schoder
Cologne Institute for Information Systems, University of Cologne
Pohligstraße 1, 50969 Cologne
schoder@wim.uni-koeln.de

Abstract

The emergence of decentralized finance (DeFi) platforms presents new avenues for studying investment dynamics in cryptocurrency markets. This paper examines portfolio performance in DeFi using a dataset from DeBank, a portfolio sharing and monitoring platform. The study focuses on the Ethereum Virtual Machine (EVM) ecosystem and covers the period from August 2023 to February 2024. It analyzes how the net worth and social influence of Web3 users relate to their portfolio performance and compares it to a benchmark index. The findings of the research indicate that an increased number of followers is statistically positively correlated with portfolio performance. This suggests that the wisdom of crowds effect may be at play. However, our findings indicated a negative correlation between net worth and performance, which challenges the prevailing hypothesis derived from previous research. These findings suggest that there are distinct patterns within the DeFi space that diverge from traditional financial market characteristics.

Keywords: DeFi, Blockchain, Web3, EVM, Social Trading

Introduction

The emergence of blockchain technology is considered a significant moment in the evolution of the digital and financial landscapes (Biais et al. 2023), similar to the transformative era initiated by the internet. The approval of the Bitcoin-Spot-ETF (The Block 2024) has notably integrated cryptocurrency assets into traditional markets, indicating a significant paradigm shift in their perception and use (Che et al. 2023). Blockchain technology, distinguished by its distributed ledger technology and smart contracts, represents, in some cases, a compelling alternative to the more centralized traditional financial systems. In particular, traditional financial institutions have encountered notable challenges, which can be attributed to their centralized nature (Hendershott et al. 2021). These challenges often manifest as inefficiencies and vulnerabilities, including, but not limited to, slower transaction times and higher costs due to intermediaries. Decentralized finance (DeFi) is at the forefront of financial innovation, leveraging blockchain technology to create alternative financial services such as lending platforms, stablecoins, and decentralized marketplaces. The ability to democratize financial services presents an unprecedented opportunity for the world's unbanked and underserved populations, advocating the principles of openness, transparency, and interoperability (World Economic Forum 2022).

Tim O'Reilly (2007) described Web2 as emphasizing the significance of user-generated content and network effects, where a product or service's value rises as more people use it. Web3, in contrast, focuses on decentralized networks, employing blockchain technology to give users ownership and control over their data, shifting the power dynamics from central authorities to individual participants. This enables users to transition from participants, as in Web2, to owners and shareholders of digital assets such as their data. Transparency and openness stand as core values of Web3, emphasizing the importance of accessible, verifiable information and democratized participation (Lai et al. 2023). These values align with the concept of social trading, which is described as a form of investment in which so-called "followers" can view and replicate the investment strategies or portfolios of other users of a social network (Gemayel and Preda 2018; Jabr and Rai 2022; Pelster and Hofmann 2018; Apesteguia et al. 2020; Yu et al. 2019).

In traditional financial markets, social influence plays a significant role in shaping investment behaviors and outcomes. Research has extensively leveraged data from social trading and analyzed the portfolio data of traders and investors within traditional financial markets. For instance, Grinblatt and Keloharju (2000) conducted studies on the investment behavior and performance of different investor types in Finland's financial market, while Feng and Seasholes (2005) explored the impact of investor sophistication and trading experience. However, since the decentralized nature of DeFi introduces unique dynamics not present in traditional markets, it remains unclear how these existing findings translate into the DeFi space. Unlike traditional markets, where centralized entities and regulatory frameworks guide investor behavior, DeFi operates on principles of openness, transparency, and peer-to-peer interactions, fundamentally altering how social influence manifests and affects portfolio performance. Despite significant market growth, portfolio performance in cryptocurrency markets has received disproportionately little academic attention. In this study, we aim to delineate similarities and differences by comparing our findings in the DeFi context with existing literature on traditional markets, thereby offering a nuanced understanding of how social influence impacts portfolio performance in these distinct financial ecosystems.

Early research in this area includes the survey by Ante et al. (2022) of German cryptocurrency investors and the studies by Gemayel and Preda (2021) and Keller and Scholz (2019) of how well cryptocurrency traders perform on a centralized exchange. Although their research is fundamental, it is limited to data from centralized exchanges and surveys. However, DeFi is now seeing billions in capital move directly on the blockchain (on-chain) (DefiLlama 2024), indicating a shift where significant crypto activities occur outside of centralized exchanges. It remains unclear whether the findings from research on centralized exchanges also hold for on-chain activities. In particular, Web3 users, those investors actively engaging with the blockchain, have been largely overlooked in current studies due to a number of challenges. The primary challenge lies in the pseudo-anonymous nature of public blockchains, which complicates the task of distinguishing between different types of wallets, such as those operated by bots, smart contracts, investors, or inactive entities. Furthermore, the multitude of distinct blockchains and the plethora of tokens and DeFi protocols present obstacles to accurately compiling data for individual wallets, particularly when it comes to compiling a comprehensive "portfolio" of such assets. While it is possible to analyze wallets based on their holdings of the native currency and widely recognized tokens, this approach fails to capture the activities associated with lesser-known protocols and tokens. This limitation in data accessibility and granularity markedly restricts the scope of research on the portfolio performance of these users.

Our research aims to fill this gap by leveraging a unique dataset from DeBank, a prominent Web3 platform that enables users to monitor and manage their DeFi investments across various blockchain ecosystems (DeBank 2024). Unlike the earlier studies, which are based on data from centralized exchanges and surveys, our dataset extends to include comprehensive on-chain activities on 57 blockchains. Furthermore, the data has been cleansed from bots, smart contracts, and entities that have been determined to be inactive. DeBank's social layer, which permits users to follow others and receive updates on portfolio progress, provides a unique perspective for our analysis. Additionally, users can purchase IDs that work like a username for their wallet, which enables us to differentiate between active Web3 users and other wallets. Our study aims to analyze these Web3 users within the Ethereum Virtual Machine (EVM) ecosystem, which accounts for approximately 90% of the total value locked (TVL) in the cryptocurrency market as of February 2024 (DefiLlama 2024). The analysis focuses on the relationship between users' net worth, social influence, and portfolio performance.

Central to our investigation is the research question, "How does portfolio performance vary among Web3 user groups?". With DeBank's unique data, including snapshots of Web3 users' net worth and their social influence (as measured by the number and summed-up net worth of their followers, the latter denominated as "Total Value Following" (TVF)) from August 2023 to February 2024, we explore this question through variance analysis methods and group comparison tests, aiming to delineate the characteristics that define Web3 users and their performance metrics. Additionally, we compare the performance of Web3 users to a volume-weighted top 15 cryptocurrency index. As a result, we contribute to the understanding of DeFi market dynamics. This contribution enriches the academic discourse on social trading and the wisdom of crowds, extending theories from the traditional financial realm to the DeFi and Web3 space. In addition, our findings have practical implications that can provide valuable insights for investors, portfolio managers, and platform developers.

Our results indicate that there is a significant difference in performance between users differentiated by social influence or wealth. While social following is associated with improved portfolio performance up to a certain point, the effect was not significant for users with the highest number of followers, challenging the simple wisdom of crowds theory. Contrary to intuitive expectations that associate wealth with high investment returns, we find an inverse relationship between wallet net worth and relative performance. These findings suggest the potential need to reassess the effects of social influence and wealth on investment success in the cryptocurrency context.

The remainder of the paper is organized as follows: We continue by deriving the hypotheses based on the current literature in the domain. Next, we explain the data and methods we used to address the research question. Then we continue by presenting and critically discussing the results of our analyses. Finally, we conclude our research and provide an outlook for further research.

Related Work and Development of Hypotheses

In recent years, numerous studies have investigated the impact of social influence on traditional stock market metrics. For example, Pelster and Hofmann (2018) examined the disposition effect on social trading platforms, revealing that traders with more followers were more prone to this bias. Similarly, Deng et al. (2023) studied social trading networks, showing that financial performance significantly influences follower behavior. These studies highlight the critical role of social proof in traditional financial markets, where centralized oversight can mitigate extreme behaviors and provide a stable environment for observing social influences.

Our research question, "How does portfolio performance vary among Web3 user groups?" specifically investigates the DeFi context, where the absence of centralized control and the pseudonymous nature of participants introduce unique dynamics. In contrast to prior research, our findings suggest that while social influence is also significant in DeFi, its effects differ due to the decentralized nature of the market. In DeFi, social proof mechanisms are more transparent and real-time but can also be subject to unique risks such as manipulative behaviors and rapid market changes.

Whereas Dorfleitner et al. (2018) and Deng et al. (2023) study social trading platforms for traditional markets like eToro and wikifolio.com, the traders in our dataset can trade across all decentralized exchanges and platforms on any EVM chain. However, they must be registered on DeBank to track their DeFi portfolios and follow other wallets on-chain. Deng et al. (2023) measure portfolio performance in terms of returns and social communication through a combined measure of sentiment, engagement with posts on eToro, likes, and other metrics. Our approach is more closely aligned with the research of Dorfleitner et al. (2018), which measures portfolio performance in terms of both returns and risk-adjusted metrics and also considers similar social metrics such as the number of followers. However, unlike these studies, which focus on direct social trading interactions, our research question, while adjacent, is specifically interested in the differences in portfolio performance between groups distinguished by both social metrics and wealth.

Social Proof and the Wisdom of Crowds

In the rapidly evolving landscape of social trading platforms, where investors can follow and replicate the portfolios of others, understanding the determinants of portfolio performance becomes of great importance. To this end, Lee and Ma (2015) introduced a system aiding users in identifying proficient traders on these platforms, highlighting the significance of expert guidance in trading decisions. Similarly, Jabr and Rai (2022) explore the dynamics of social trading platforms and their impact on the disposition effect among individual traders in the case of foreign exchange (forex) trading. Thereby, their study focuses on how two key social features of these platforms (views and followers) influence traders' tendencies to sell assets at a gain too early (realizing gains) and to hold onto losing assets for too long (avoiding losses). They found that these social cues can both amplify and mitigate the disposition effect, depending on market conditions. Additionally, the studies of Pelster and Hofmann (2018) and Deng et al. (2023) both obtain data from eToro, one of the largest social trading platforms, observing the dynamics of the number of followers and investment actions. While Pelster and Hofmann (2018) find that forex traders with more followers are more prone to the disposition effect than investors who are not followed at all, Deng et al. (2023) reveal that followers focus mainly on financial performance when deciding to continue following one specific trader. In this regard, the nuanced understanding of how social features like the number of followers impact user behavior on traditional social trading platforms motivates our exploration of Web3 social trading platforms.

Furthermore, the study by Dorfleitner et al. (2018) offers an in-depth analysis of the performance dynamics on social platforms for stock and contracts for differences (CFD) trading, examining the relationship between trading behaviors and the returns of signal providers (traders). Building upon their insights, it becomes relevant to formulate the hypothesis that the number of followers a trader has could be indicative of the trader's performance. Despite a lack of direct evidence for the wisdom of the crowd effect in enhanced returns through follower counts, the exploration by Dorfleitner et al. (2018) into social trading dynamics sets a foundation for further inquiry. Particularly, of how it behaves with other social trading platforms (e.g., Web3 platforms) and other assets than stocks and CFDs, whose unique dynamics may enhance or weaken this wisdom of the crowds effect.

The investigation into the wisdom of crowds by Wagner and Vinaimont (2010) provides a nuanced foundation for understanding collective intelligence and its implications for predictive accuracy across diverse domains, including finance and information systems. Their empirical analysis and subsequent simulations demonstrate that collectives, even those composed of non-experts, can achieve expert-like performance under specific conditions, such as diversity, independence, and decentralization of opinions. With these insights into the wisdom of the crowds, we deduce that the crowd identifies profitable Web3 users, which is why we assume a higher follower count to be a good proxy for enhanced portfolio performance. The notion that a larger follower base could serve as a form of social proof, suggesting trust and confidence in a portfolio, provides a compelling rationale for defining our first hypothesis:

> ***H1:*** *Web3 users with more followers are associated with better portfolio performance, indicating a wisdom of crowds effect in Web3.*

This hypothesis posits that the collective intelligence of the crowd is adept at recognizing Web3 users who exhibit superior portfolio performance. Although a direct link between the number of followers and trading returns might not be straightforward, it suggests that social dynamics, such as the wisdom of the crowd, play a significant role in finding successful Web3 users. Thus, the social endorsement reflected by a substantial follower base is more a consequence of the crowd's ability to identify profitable Web3 users than the cause of improved portfolio performances.

Web3 Users' Wealth and their average Followers' Wealth

The study of Han and Kumar (2013), demonstrating that stocks heavily traded by retail investors underperform, supports the notion that investors' characteristics significantly influence portfolio performance. Lower-net-worth investors, akin to retail investors, could be more prone to speculative investments driven by overconfidence or the pursuit of quick gains, often leading to suboptimal asset selection and underperformance. This pattern, observed in traditional markets due to speculative behaviors among retail investors, can also be applied to the cryptocurrency market. To this end, Łęt et al. (2022) analyze the informational efficiency of the cryptocurrency market through the lens of fundamental factors for Bitcoin and Ethereum. Their findings of informational inefficiencies in these markets highlight the potential for active trading strategies, based on structural indicators, to outperform passive ones. This inefficiency, characterized by the ability of certain strategies to generate excess returns, implicitly endorses the notion that investors' characteristics, such as their net worth, could remarkably point to their ability to exploit these inefficiencies.

The research by Grinblatt and Keloharju (2000) into the investment behavior and performance of various investor types in Finland's financial market finds distinct behavioral patterns among investor types based on their sophistication level. The study also relates investor's sophistication to their investment size (wealth invested in stocks). On the one hand, Grinblatt and Keloharju (2000) identify sophisticated investors exhibiting momentum investing by buying past-winning stocks and selling past losers. Conversely, less sophisticated investors showed a tendency towards contrarian investing, often buying past losers and selling winners. These disposition effects, a behavioral bias where investors demonstrate a tendency to hastily realize gains while hesitating to acknowledge losses, have also been studied by Feng and Seasholes (2005). Particularly intriguing is their finding that while sophistication and experience markedly diminish the tendency to avoid losses, they only partially alleviate the tendency to realize gains. This implies that sophistication can reduce disposition effects, which can also offer profound implications for understanding investor behavior in the cryptocurrency market.

The disparity in investment behavior suggests that, as the previous two studies mentioned, an investor's wealth can serve as a partial proxy for an investor's level of sophistication, which is crucial in determining investment performance. Understanding that wealth accumulation often parallels increased sophistication, our hypothesis posits that higher-net-worth Web3 users, representing a greater level of sophistication and experience, are better positioned to circumvent the pitfalls of behavioral biases such as the disposition effect. This, in turn, translates to superior portfolio performance compared to their less wealthy counterparts by, e.g., having greater capacities to absorb larger fluctuations in the market, allowing them to hold onto investments longer or to invest in higher-risk, higher-reward assets without the immediate need to liquidate for cash flow reasons. Therefore, combining the insights from the literature, we posit our hypothesis:

> ***H2:*** *Web3 users with more net worth are associated with better portfolio performance than Web3 users with less net worth.*

Building on the same rationale for H2, we can logically extend this premise to the composition of the Web3 users' social following. If higher net worth is associated with higher investor sophistication, as suggested by Grinblatt and Keloharju (2000), it follows that high-net-worth individuals are more likely to identify and follow users with superior portfolio performances compared to less sophisticated individuals. The dataset comprises Web3 users, each associated with the following two social metrics: 1) their "Total Value Following" (TVF) and 2) their total number of followers. The TVF represents the aggregated net worth of all the user's followers. To calculate the average net worth per follower, called the "average TVF", we divide the user's TVF by the user's total number of followers. We approximate the average net worth of a user's followers with the average TVF variable and posit the following hypothesis:

> ***H3:*** *Web3 users with higher average TVF are associated with better portfolio performance than Web3 users with lower average TVF.*

Following the formulation of our hypotheses, it's crucial to clarify that our approach does not imply causation between the number of followers, net worth, or average TVF and portfolio performance. Our study is designed to observe associations without making definitive claims about the underlying reasons for variations in performance. In this study, users were categorized into groups based on their initial net worth, follower counts, and average TVF from the first snapshot of our time series data. This early categorization is essential for preventing assumptions that inherently superior investment performance could lead to an increase in followers or a higher net worth. By establishing these groupings at the beginning of our study, we aim to examine the relationship between the initial baseline characteristics and subsequent investment performance, thereby addressing potential confounding effects.

Data

This study uses a dataset from DeBank, a prominent Web3 platform, where each entry corresponds to a unique wallet address. DeBank is a DeFi portfolio management platform that offers users the ability to track and manage their DeFi wallet balance across multiple blockchain ecosystems. Their service also targets the challenge of distinguishing authentic and valuable users from Sybil addresses, airdrop hunters, and bots, which tend to have low net worth and obscure the true users within the dataset (DeBank 2024).

The dataset comprises Web3 user net-worth snapshots spanning from August 2023 through February 2024. It specifically includes users who satisfy one or more of the following criteria: a net worth greater than 1000 $USD, the ownership of a "Web3 ID," or the possession of followers on DeBank whose total net worth exceeds zero. This dataset spans 57 EVM (Ethereum Virtual Machine) compatible chains, which collectively account for approximately 90% of the Total Value Locked (TVL) in the cryptocurrency market as of February 2024, as reported by DeFiLlama (2024).

Example dataset entries for users are presented in Table 1. Each user is identified with a unique EVM wallet address. The “net worth”, as reported by DeBank, includes the summed-up asset worth on all supported chains, including token values in $USD and assets deposited in protocols like staking and liquidity pools or lending platforms across most EVM chains. In the following, net worth is also referred to as wealth.

Besides portfolio tracking, DeBank also offers a social layer where users can sign into their platform with their wallet and follow other wallets to get notified about their activities, such as trades on the supported blockchains. Web3 ID is a product released by DeBank, similar to ENS domain names. Users can find a standard word with a length of 4 to 15 characters as their ID and mint it after paying $96. This social layer enables us to access data such as a user’s follower count, Total Value Following (TVF), which is the summed-up net worth of a user’s following wallets, and the calculated average TVF. Updates to the dataset were made with varying frequency, ranging from weekly to monthly intervals.

Additionally, we received labels from the service walletlabels.xyz, which has labeled over 60 million wallets on EVM chains (WalletLabels.xyz 2024). These labels include manual labels assigned to known protocols or exchange addresses but also labels assigned based on heuristics to identify smart contracts, token contracts, bots, and others.

The raw dataset contains over 3,600,000 unique wallets, out of which around 53,000 minted a web3 ID on the DeBank platform.

EVM Wallet Address	Snapshot Date	Net Worth/ Wealth ($USD)	Followers	TVF ($USD)	Avg. TVF ($USD)	Web3 ID
0x540d97e....	2023-09-22	4,753	656	1,213,720	1,850	Pampidu
0x5efa253b....	2024-01-22	349,302	5	49,517	9,903	mlrl

Table 1. Example Web3 User Entries

Method

We aimed to identify significant differences in the performance of Web3 users’ portfolios by examining their attributes, including follower count, net worth, and average TVF, via group comparison tests. Users were grouped by these attributes within the dataset: follower counts were categorized into four groups, ranging from fewer than ten to over three hundred followers, while net worth and average TVF were divided into tiers that represent a progression from four-figure to over six-figure portfolios, as they provide intuitive financial thresholds. Due to the non-normal distribution of our data, which prohibits the use of traditional

ANOVA, the Kruskal-Wallis test was applied to assess differences between the groups' distributions. In cases of significant differences, the nature of the performance differences was examined in detail. Additionally, the performances were benchmarked against a volume-weighted crypto index.

We began by excluding wallets labeled by walletlabels.xyz as entities, such as smart contracts, deposit wallets, and exchange wallets, thereby increasing the chances of observing actual users. Next, we extracted the following variables for each wallet address/user:

- Net worth/Wealth, which is the sum of all balances across all chains (in $USD).
- Follower Count.
- Average TVF, which is the TVF divided by the follower count as a means to estimate the average net worth per follower (in $USD).
- Portfolio performance between August 2023 and February 2024 (Log returns and Sortino ratio)

We categorized the data from the first snapshot into wealth groups, follower count groups, and average TVF groups. The reason for using the initial snapshot for categorization was to reduce the impact of confounding effects that may occur over time. The portfolio performance of each user was measured from the categorization snapshot onward. This approach enabled us to observe the relationship between performance and our independent variables from a baseline established at the beginning of our observation period. The wallets were categorized based on the following criteria:

- Follower Count, categorized into: <10, 10-100, 100-300, and >300 followers.
- Average TVF, segmented into: None, 1K-10K, 10K-100K, 100K-500K, and >500K $USD categories.
- Wealth Groups, organized by net worth: 0.1K-10K, 10K-100K, 100K-1M, and >1M in $USD.

The division into the aforementioned follower count groups captures the majority of the distribution. Table 2 reveals that the majority of followers fall within the range of 0-500. There is, however, a very long tail, with some extreme outlier accounts that have up to 50K followers, which we will address later. These are typically accounts from influencers and well-known wallets, such as the Ethereum Foundation. The logic for the first bucket being <10 is because on Debank occasionally one gets a follow from an account relating to a DeFi product to advertise themselves. Setting the lower boundary at <10 filters such occurrences out.

The logarithmic portfolio returns were calculated from the first to the last snapshot to analyze performance over time. The Sortino ratio S was used as a risk-adjusted measure of return, focusing on downside deviation rather than total volatility. It specifically targets downside deviation, offering a nuanced view of risk by distinguishing harmful volatility from potentially beneficial movements. Unlike other risk-adjusted measures such as the Sharpe ratio, which penalizes all volatility regardless of its direction, the Sortino ratio recognizes that upside volatility represents favorable market dynamics that are advantageous to investors. It is defined as:

$$S = \frac{R - T}{D}$$

where R is the asset or portfolio average realized return, T is the target return or risk-free rate (set to 0 in our case due to the unique characteristics of the DeFi market, where traditional risk-free assets are absent, market volatility is high, and using a 0% rate simplifies comparisons in our case), and D is the downside deviation, which is defined as:

$$D = \sqrt{\frac{1}{N}\sum_{i=1}^{N} min(0, r_i - T)^2}$$

where r_i represents the individual returns in the series, N is the total number of observations in the return series, $min(0, r_i - T)^2$calculates the square of the minimum of zero and the excess return $r_i - T$, isolating negative returns below the target T and squaring them, and the square root of the average of these squared deviations represents the downside deviation (Sortino and Price 1994).

To manage anomalies in the log returns and Sortino ratio variables, we applied the Interquartile Range (IQR) method. This method is particularly useful for managing anomalies in financial data, which can be skewed and have extreme outliers. By setting bounds at Q1 - 10IQR and Q3 + 10IQR, we filtered out data points that could distort our analysis. This allowed us to focus our study on more representative wallet activities. After these initial steps, our dataset was narrowed down to 1,139,275 entries.

Although analyzing the entire dataset may seem intriguing, attributing portfolio performance to any EVM wallet comes with significant uncertainties. The main issue is the inability to determine whether individual users use these wallets for portfolio management or whether the wallets have other uses. To ensure the integrity of our analysis, we narrowed the scope of our study to wallets associated with DeBank Web3 IDs. This selection criterion is grounded in the confidence that these wallets, by nature of their IDs, are actively used for portfolio tracking and sharing within the platform, as this is the primary functionality of the DeBank service. Additionally, we only considered wallets with a net-worth over 100 $USD due to the high amount of noise in the data from wallets with smaller balances. This approach narrows our research scope to wallets that are not only involved with DeFi platforms but also likely reflect individual users managing their cryptocurrency portfolios. This strategic limitation leaves us with 34,460 entries, providing a more precise and accurate sample for examining our research question.

We proceed by addressing our hypotheses and testing whether there is a statistical difference between the groups regarding portfolio performance. The standard procedure for this task would be ANOVA, which has assumptions like normality and variance homogeneity. The Anderson-Darling test and Levene test were used to assess data normality and variance homogeneity, respectively. Both tests rejected the null hypothesis, indicating that the data did not follow a normal distribution and exhibited variance heterogeneity. The analysis proceeded with the Kruskal-Wallis test (Kruskal and Wallis 1952), a non-parametric method suitable for our dataset's characteristics as an alternative to ANOVA, as in prior work such as Mnif et al. (2021), Jarno and Kołodziejczyk (2021), and Caporale and Plastun (2019). Therefore, the null hypothesis to investigate whether two or more independent samples from different groups originate from the same distribution is formulated as:

$$F_1 = F_2 = \ldots = F_k$$

with the alternative being:

$$F_i \neq F_j \; for\ at\ least\ one\ pair$$

Because this method only tells us whether there is any difference between the group distributions, we need to proceed with a pairwise comparison. For this, we utilized the multiple rank sum post-hoc Dunn tests following the Kruskal-Wallis analysis, which is a standard procedure (Pohlert 2014).

We visualized the results to identify the nature of potential differences between groups to address hypotheses H1 to H3. Finally, the portfolio performances were compared to a volume-weighted crypto market index of the top 15 cryptocurrencies (excluding stablecoins).

Table 2. depicts the descriptive data of our processed dataset.

	Net Worth ($USD)	**Follower Count**	**Average TVF ($USD)**	**Log Returns**	**Sortino Ratio**
count	34460	34460	34460	34460	34460
mean	68821	449	20614	0.615	2.692
std	1238212	1277	176788	1.047	3.836
min	100	0	0	-9.452	-1.000
25%	736	19	1299	0.175	0.532
50%	2278	131	2788	0.593	1.545
75%	8608	435	6768	1.130	3.224
max	131777442	54131	15713720	6.716	31.415

Table 2. Descriptive Statistics on the Dataset

Results

For all reported statistics: * = P ≤ 0.05, ** = P ≤ 0.01, *** = P ≤ 0.001.

	Hypothesis Test Log Returns	**Hypothesis Test Sortino Ratio**	**Results**
Follower Count	Kruskal-Wallis H-test statistic: 103.80 P-value: **2.358e-22*** **	Kruskal-Wallis H-test statistic: 14.22 P-value: **0.003** **	Performance differentiates significantly for wallet groups with different follower counts
Average TVF	Kruskal-Wallis H-test statistic: 325.64 P-value: **3.183e-69*** **	Kruskal-Wallis H-test statistic: 175.851 P-value: **5.799e-37*** **	Performance differentiates significantly for wallet groups with different average TVF
Wealth	Kruskal-Wallis H-test statistic: 1081.73 P-value: **3.344e-234*** **	Kruskal-Wallis H-test statistic: 554.928 P-value: **5.938e-120*** **	Performance decreases significantly with increasing wealth

Table 3. Kruskal-Wallis Results Summary

The Kruskal-Wallis test results in Table 3 show that, concerning log returns and Sortino ratios, at least two groups differ in their distributions across all examined variables (wealth, follower count, and average TVF) at the 0.1% significance level, except for the follower count for the Sortino ratio, which is significant at the 1% level. Therefore, we proceed with the pairwise comparison for all groups.

Follower Count

< 10	1.000 / 1.000			
10 - 100	**0.000***** / 0.109	1.000 / 1.000		
100 - 300	**0.000***** / **0.000*****	**0.002**** / **0.021***	1.000 / 1.000	
> 300	**0.000***** / **0.034***	**0.002**** / 0.652	0.652 / **0.042***	1.000 / 1.000
Follower Count	**< 10**	**10 - 100**	**100 - 300**	**> 300**

Table 4. Dunn's test follower count p-values Log Returns / Sortino Ratio

For log returns, the Dunn's test results in Table 4 are significant for all pairs except the 100–300 and >300 follower groups. The results for the Sortino ratio are significant between all pairs except 10-100 and >300 and 10-100 and <10 follower groups.

When plotting the medians of each group, we can see a similar pattern for both log returns (Figure 1) and the Sortino ratio (Figure 2): A minor increase (16% and 11%, respectively) in performance with an increase in followers but diminishing performance for over 300 followers regarding log returns and even a 7.8% decrease for the Sortino ratio. This is especially true for the long tail, where performance continually decreases for enormous follower counts, down to a median Sortino ratio of 0.8 for wallets with 20K-30K followers. Therefore, we can partially confirm hypothesis H1 for the majority of wallets, which assumes an increase in performance for users with more followers for numbers below 300 followers.

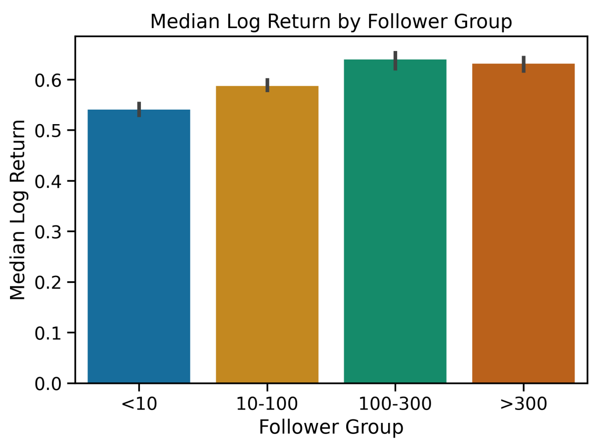

Figure 1. Median Log Return (Followers)

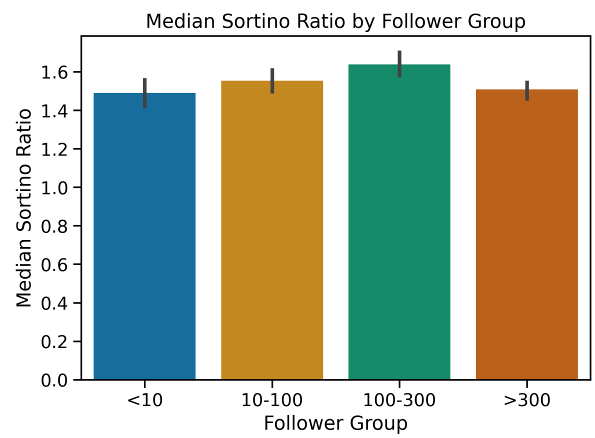

Figure 2. Median Sortino Ratio (Followers)

Average TVF

None	1.000 / 1.000				
1K-10K	**0.000*** /** **0.000*** **	1.000 / 1.000			
10K-100K	0.092 / **0.000*** **	**0.000*** /** **0.000*** **	1.000 / 1.000		
100K-500K	**0.000*** /** 0.303	0.467/ 0.181	**0.000*** /** **0.000*** **	1.000 / 1.000	
> 500K	**0.000***/** **0.000*** **	**0.006**/** **0.010** **	**0.000***/** **0.000*** **	**0.005**/** **0.003** **	1.000 / 1.000
Average TVF	**None**	**1K-10K**	**10K-100K**	**100K-500K**	**> 500K**

Table 5. Dunn's test average TVF p-values Log Returns / Sortino Ratio

Multiple patterns are evident from the results for the average TVF in Table 5. The comparison between the > 500K group and all other groups is significant. Furthermore, Figures 3 and 4 show that the group's performance exceeds that of all other groups. For the other groups, the Dunn's test is significant in most cases except for the comparison between the 1K-10K and 100K-500K groups, which also exhibit similar performances.

Furthermore, it is not significant for the "None" group compared to 100K-500K and 10K-100K for the Sortino ratio and log returns, respectively, which leads to a partial rejection of hypothesis H3. There is no discernible pattern between most groups; however, the >500K group is significantly different from all other groups and exhibits the highest performance in both log returns and Sortino ratio.

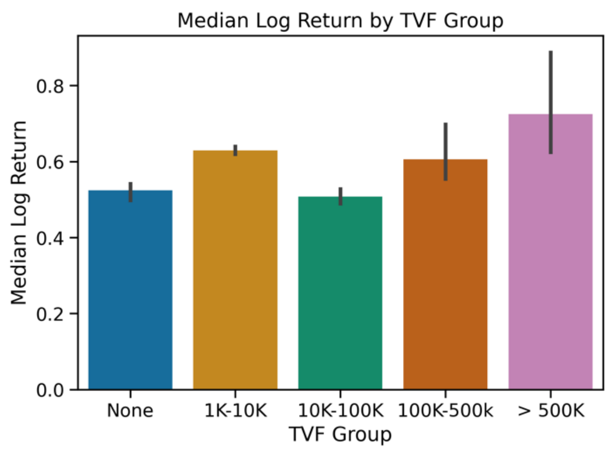

Figure 3. Median Log Return (avg. TVF)

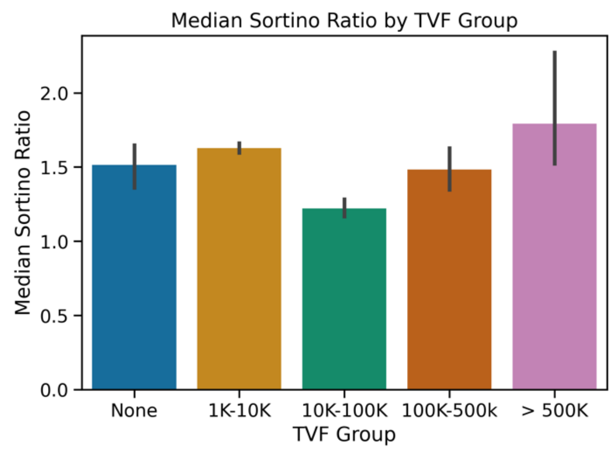

Figure 4. Median Sortino Ratio (avg. TVF)

Wealth

0.1K-10K	1.000 / 1.000			
10K-100K	**0.000***** / **0.000*****	1.000 / 1.000		
100K-1M	**0.000***** / **0.000*****	**0.000***** / **0.000*****	1.000 / 1.000	
> 1M	**0.000***** / **0.000*****	**0.000***** / **0.000*****	0.097 / **0.017***	1.000 / 1.000
Portfolio Net Worth ($USD)	**0.1K-10K**	**10K-100K**	**100K-1M**	**> 1M**

Table 6. Dunn's test wealth p-values Log Returns / Sortino Ratio

For the net worth variable, the results of the pairwise comparison (Table 6) are all highly significant except for the log returns between the 100K-1M and >1M groups. Furthermore, when examining the medians in Figures 5 and 6, a considerable decrease of around 40% in performance is observable with decreasing portfolio size across the log returns and Sortino ratio, respectively. This leads to a rejection of H2, as the presumed relationship is not only nonexistent but inverse, with a large drop in median performance across the wealth groups.

Figure 7 presents the distribution of Sortino ratios across different wealth groups. Each distribution is skewed towards higher Sortino ratios but varies significantly in kurtosis. The wealthier groups display a lesser concentration in the high Sortino ratio tail, with the >1M group having a mode close to 0, indicating a predominance of lower Sortino ratios. In contrast, the 100K-1M group shows a mode closer to 1, with a more symmetric distribution that suggests varied performance. The groups with smaller portfolios, the 10K-100K and 0.1K-10K groups, exhibit the broadest peaks, with numerous observations between Sortino ratios of 2 and 3, reflecting a wider spread of higher ratios. These patterns indicate that lower wealth groups tend to achieve higher and more variable Sortino ratios, whereas the distributions for higher wealth groups are more clustered around lower values.

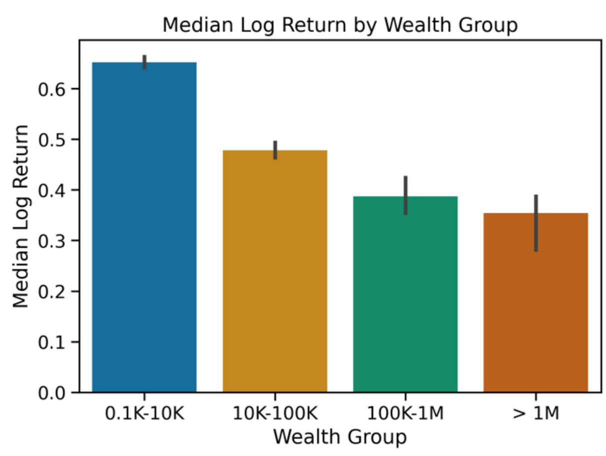

Figure 5. Median Log Return (Wealth)

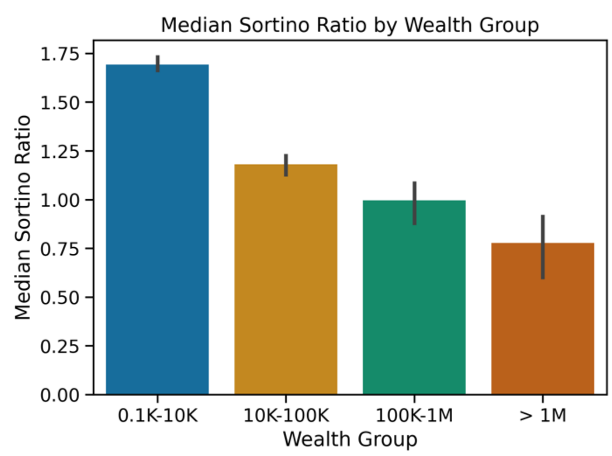

Figure 6. Median Sortino Ratio (Wealth)

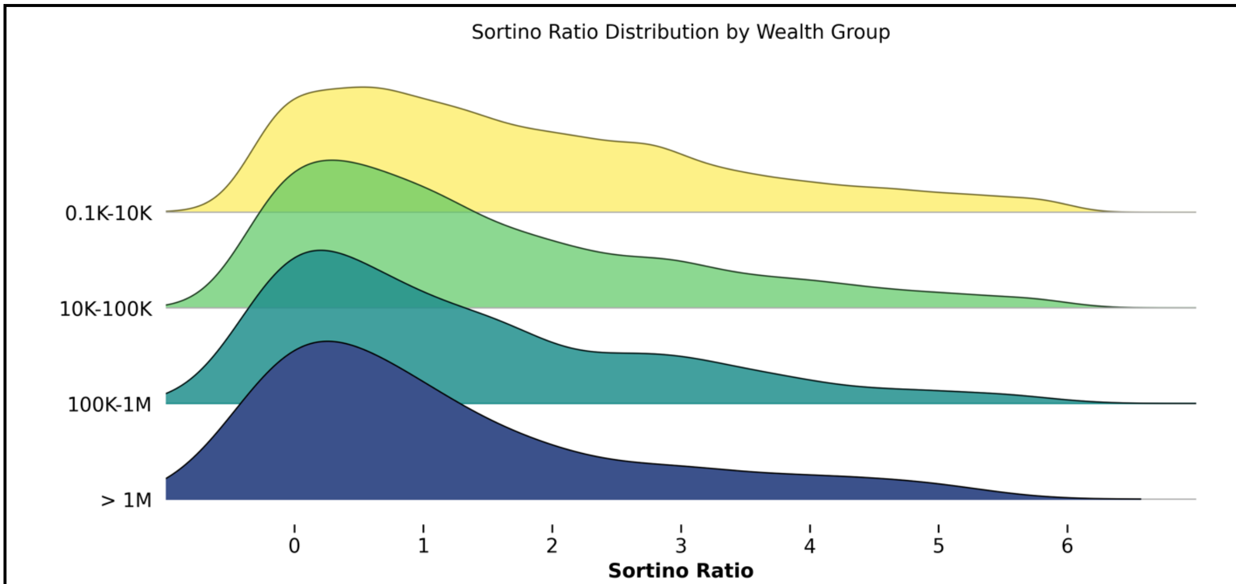

Figure 7. Sortino Ratio Distribution by Wealth Group

During the study timeframe, the crypto index achieved a Sortino ratio of 2.15, a cumulative return of 98%, and a log return of 68%. Figure 8 displays the comparison between the median cumulative returns of all Web3 users, including the 25th to 75th percentile ranges, and the cumulative index returns. It is evident that Web3 users always underperform the index (in the median). However, due to the compounding effects, the variance in performance (as indicated by the diverging IQR) is increasing over time. Prior to November

2023, the 75th percentile underperformed the index. However, after that point, an increasing number of users began to outperform the index, with the 75th percentile reaching approximately 200% cumulative returns.

When comparing the percentage of users outperforming the volume-weighted crypto index, it was found that 39.56% outperformed in terms of the Sortino ratio. Considering the subgroups, the subgroup with an average TVF of over 500k had the highest outperformance ratio of 45.09%, while the group with a net worth of over 1M $USD had the lowest ratio of 21.97%. In terms of log returns, the results show an overall outperformance of 44.46%. The group with the best performance (average TVF >500k) had a ratio of 53.12%, while the worst-performing group (net worth >1M) had a ratio of 16.88%.

Discussion

The analysis conducted on the relationship between follower count, log returns, Sortino ratios, and the average TVF presents intriguing insights into the dynamics of social trading and portfolio performance within cryptocurrency markets. Our findings reveal nuanced patterns that both confirm and challenge pre-existing hypotheses concerning the association of social influence, net worth, and portfolio performance.

Our results lend partial support to the Follower Hypothesis (H1), highlighting a complex relationship between a user's follower count and the user's portfolio performance. Consistent with our expectations, there is a discernible increase in both log returns and Sortino ratios as the follower count rises for the group with up to 300 followers. Beyond this threshold, we observe a decline in performance metrics, suggesting diminishing returns for users that attain high levels of popularity. This finding is consistent with Dorfleitner et al. (2018), which found a downturn in performance among traders with a higher follower count, aligning with the insights from Pentland (2013). Drawing on data from eToro in 2011, Pentland's research highlighted that traders factoring in the activities of their peers realized a 30% profit increase over those who merely aligned with the most followed traders. This discrepancy can be attributed to a diminishing social learning effect, where the most popular traders potentially suffer from overconfidence, impacting their decision-making and, ultimately, their performance. To this end, we can partially confirm H1. We observe an evident increase in performance with an increase in followers, suggesting a wisdom of the crowds effect; however, this is not the case for the users with the highest number of followers. As mentioned before, the data exhibits a long tail regarding the follower count. While most accounts have fewer than 500 followers, some have follower counts of 50K or more. The presented findings, however, are consistent. Performance consistently and drastically decreases as follower counts exceed 300. Furthermore, the

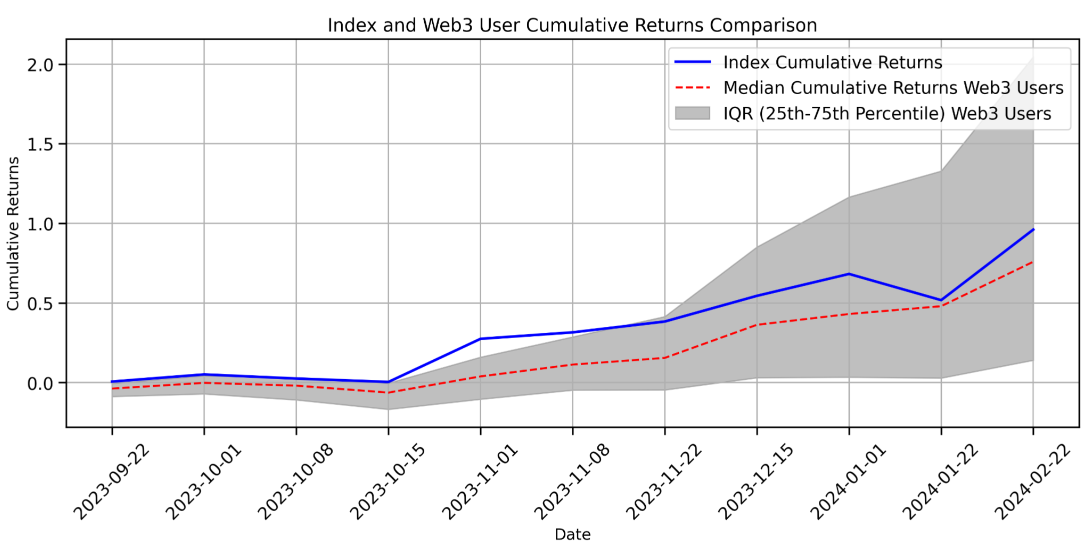

Figure 8. Index and Web3 User Cumulative Returns Comparison

difference in performance between groups is minor, even though a general trend exists. Several potential explanations emerge for the observed decline in portfolio performance among the most-followed group. A manual examination of these high-profile wallets indicated that they predominantly held large-scale portfolios, often exceeding millions of dollars, with the majority of funds allocated to farming protocols to generate steady yields. This suggests that these investors may have previously achieved significant investment returns, which helped them attract a large follower base. Over time, however, they appear to have shifted towards strategies focused on capital preservation. Additionally, many of these wallets were linked to handles on x.com and other social media platforms in their profiles, accompanied by substantial follower counts on these sites. This suggests that a sizable portion of their DeBank followers may have come from social media marketing rather than from organic growth on the platform due to superior investment performance.

The patterns regarding average TVF and performance are less clear-cut. While the highest average TVF correlates with superior performance, delineating a consistent trend across lower TVF groups is not straightforward. Notably, users in the 1K-10K TVF range exhibit the second-highest performance, with the "None" group surprisingly outperforming other categories. Nonetheless, the significant outperformance of the group with an average TVF of over 500k indicates that there are wealthy followers on the DeBank platform who manage to identify high-performing users. The observation that users with the largest average TVF performed best does validate our hypothesis regarding the association with TVF, but only to an extent. Thus, we can partially reject H3, as it only holds for certain subgroups.

Contrary to initial expectations, our analysis unveils a reverse trend in performance across different wealth groups, with a performance decrease observable from the lowest to the highest net worth group. This discrepancy to insights from traditional markets may be attributed to the different risk profiles and investment opportunities in DeFi, where high-risk, high-return strategies are more accessible and often more rewarding for smaller investors. In contrast, traditional markets favor more stable, lower-risk investments, which benefit larger portfolios. The unexpected trend holds for both log returns and the Sortino ratio, indicating a higher net worth may not necessarily translate to higher performances. This could be reflective of the inherent challenges in generating high returns on larger portfolios due to liquidity constraints or a strategic shift towards capital preservation and yield generation in larger wallets. We reject H2, as the hypothesized relationship between net worth and performance appears to be inverse. Several explanations can be posited for the findings regarding net worth. The observed time frame is characterized by an extreme bull market, allowing users with a high-risk appetite to outperform more conservative, calculated strategies. Systematic spot checks of particularly well-performing low-net-worth users showed that they had taken highly concentrated bets on low-market-cap projects and meme tokens, which performed particularly well during the studies' market phase. High-net-worth users, however, were in many cases rather diversified across large-capitalization coins and also held bigger shares of stablecoins. This suggests a potential variance in performance based on market conditions, underscoring the need to replicate this study across different market cycles, including bear regimes where the reflexive nature of the cryptocurrency market produces larger negative returns for the aforementioned low-caps and meme tokens. Additionally, it is plausible that larger wallets are not primarily used for active investments but rather for the preservation of capital, with profits being transferred to these wallets for safekeeping. This practice could obscure the true investment activities of individuals behind these wallets, as high-risk, high-return investments may occur in smaller wallets.

Nonetheless, the structural differences between cryptocurrency markets and traditional financial markets suggest that patterns observed in traditional markets, such as the correlation between investor performance and wealth, might not directly translate to the cryptocurrency space. This is indicated by the outperformance of smaller users in terms of the Sortino ratio, a risk-adjusted performance metric. Although higher returns for smaller portfolio sizes during bullish market phases were expected—due to fewer liquidity constraints and a tendency towards riskier, more concentrated bets—the Sortino ratio should adjust for these effects by penalizing large volatility and portfolio fluctuations. The fact that larger portfolios do not demonstrate clear outperformance in the Sortino ratio but instead show a pattern similar to log returns suggests that smaller investors may exhibit a more calculated investment approach than expected. The unusual outperformance observed among investors with DeBank Web3 IDs suggests a need for further investigation to determine whether this reflects inherent skill, specific market conditions, or a combination of both. Future studies should expand the dataset to include a more diverse sample. We only had access to aggregate portfolio data in our study; however, a detailed breakdown of assets held could provide insights into the nature of performance differences. Quantitative analyses that control for investment adjustment volume and the proportion of unstable assets could help determine whether liquidity issues or a preference for stablecoins among wealthy investors contribute to their relatively lower financial returns compared to less wealthy investors actively seeking high returns.

It is noteworthy that a remarkable portion of users in our study managed to outperform a designated crypto index, with approximately 39.6% of users surpassing the index in terms of the Sortino ratio and 44.5% in terms of log returns. This indicates a relatively high level of performance among the studied users, surpassing typical numbers in traditional financial markets (Ganti et al. 2023). However, the majority would still benefit more from holding an index. Interestingly, the numbers of outperformance in terms of returns closely match the findings of Ante et al. (2022), who found that around 44% of surveyed cryptocurrency investors outperformed Bitcoin even though their survey was conducted before our study and covered different market regimes, including bear markets. Returning to the research question "How does portfolio performance vary among Web3 user groups?" we conclude that there is a significant difference in performance between different groups in association with attributes such as the number of followers and net worth.

Conclusion and Outlook

In this research, we analyzed the portfolio performance within the Web3 ecosystem, exploring its associations with social factors and wealth. Our analysis, grounded in a unique dataset from DeBank, sheds light on the dynamics of the net worth of Web3 users, their follower counts, and the summed-up net worth of their followers.

This study makes significant theoretical and practical contributions to the DeFi sector by examining the dynamics of social trading and portfolio performance in the Web3 environment. From a theoretical perspective, our research extends the understanding of the "wisdom of crowds" in Web3 social trading contexts. Our findings confirm that an increase in follower count generally corresponds with improved performance, a result that is consistent with similar findings in studies from other financial domains. Additionally, the study emphasizes the significance of follower quality by highlighting the superior performance of users with the highest average TVF. This suggests that not just the number but also the net worth of followers can be a profound indicator of portfolio performance. However, our investigation suggests that the presumed connection between wealth and investor sophistication and, by extension, performance does not hold in our sample, challenging existing assumptions and inviting further inquiry. Our study specifically examines the correlation between user characteristics and portfolio performance. However, future research should explore these relationships in both directions to enhance theoretical contributions. Returns and wealth can influence follower accumulation, while follower growth might also affect returns and wealth. Given the endogeneity of the data generation process, leveraging temporal dynamics can help characterize the interplay between social and financial aspects. Ultimately, it is crucial to examine the causal mechanisms behind our observations. By analyzing changes in follower count and net worth over time, researchers can gain valuable insights into how these factors impact performance under different market conditions.

Practically, the findings of this study provide valuable insights for practitioners and Web3 users by identifying the performance characteristics of profitable wallets. We demonstrate that, despite a portion of users outperforming the market, the majority would benefit more from adopting index investment strategies, highlighting the efficiency and potential safety of such approaches in the crypto domain. This information is of significant importance to educators and policymakers who are attempting to navigate the rapidly growing interest in cryptocurrencies among retail investors. Our results not only guide investment strategies but also contribute to ongoing discussions about the viability and management of investments in the Web3 space.

While our study has produced interesting findings, it is crucial to recognize the necessity for additional research in this field due to certain limitations encountered during our investigation. Our dataset primarily covers a bull market period, specifically from August 2023 to February 2024, which was influenced by major market events like the approval of the Bitcoin spot ETF. This period may not accurately capture the intricacies and variations observed in various market conditions. Further research should investigate the impact of social factors, net worth, and portfolio performance in various market conditions, including bear markets, to evaluate the strength of our results. We conducted a study that specifically examined the connections between user characteristics and investment performance, without making any claims about causation. Future studies should focus on revealing the causal relationships behind these associations using methodologies like quantitative analyses or natural experiments. In addition, our analysis primarily centers on wallets linked to a Web3 ID, which may not provide a comprehensive view of the wider DeFi ecosystem. Including wallets without a Web3 ID in the scope could provide a more comprehensive perspective. However, this approach presents difficulties in verifying wallet ownership and accurately attributing portfolio performance to individual users. Establishing reliable techniques for confirming wallet ownership will be essential for future research.

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