# Stranger Danger? Investor Behavior and Incentives on Cryptocurrency Copy-Trading Platforms

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## ABSTRACT

Several large financial trading platforms have recently begun implementing "copy trading," a process by which a leader allows copiers to automatically mirror their trades in exchange for a share of the profits realized. While it has been shown in many contexts that platform design considerably influences user choices—users tend to disproportionately trust rankings presented to them—we would expect that here, copiers exercise due diligence given the money at stake, typically USD 500–2 000 or more. We perform a quantitative analysis of two major cryptocurrency copy-trading platforms, with different default leader ranking algorithms. One of these platforms additionally changed the information displayed during our study. In all cases, we show that the platform UI significantly influences copiers' decisions. Besides being sub-optimal, this influence is problematic as rankings are often easily gameable by unscrupulous leaders who prey on novice copiers, and they create perverse incentives for all platform users.

## CCS CONCEPTS

**• General and reference → Measurement**; **• Human-centered computing → Empirical studies in HCI**; **• Applied computing → Digital cash**.

## KEYWORDS

Copy Trading, Social Trading, Online Markets, Cryptocurrency, Bitcoin, Trading, Derivatives

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## 1 INTRODUCTION

Making investment decisions on complex financial products is both difficult and time consuming. In particular, modern investment instruments with potentially high rewards (and equally high risks), such as cryptocurrencies and their derivative products, operate in 24/7 markets, and often present tremendous volatility. Fortunes can be made, or lost, in mere hours. Hence, prudent investing requires not only time spent learning the complexities of the market, but close attention to constantly monitor events, news, and market movements.

To alleviate this burden, in the late 2000s, several financial trading platforms—e.g., eToro,[1] ZuluTrade,[2] and ayondo,[3] among others—started offering "*copy trading*," also known as "social trading." Copy trading allows (novice) investors, or *copiers* (also known as "followers") to delegate investment decisions and passively benefit from the expertise of a *leader* (or signal provider) in exchange for a share of any realized profit. The concept of delegation itself is not new—portfolio managers have, for decades, performed similar services—but copy trading takes it to an extreme, by letting any *copier* follow any *leader* at the click of a button. Importantly, no endorsement or credentials are needed to become a leader: anybody can play that role, as long as somebody is willing to copy their portfolio and trades.

Copy trading has gained increased attention and popularity in the recent past. For instance, in 2023, Twitter announced a forthcoming partnership with eToro to offer copy-trading services [12]. Cryptocurrency investment, in particular, is an area where copy trading has surged in popularity, due to the large number of traders and considerable investment risks leading to high potential upsides [39, 63]. Several crypto exchanges launched copy trading services on their platforms, claiming that they offer environments where individuals can successfully invest without having to pay close attention to price movements and without any deep knowledge of finance. In particular, the top three cryptocurrency exchanges at the time of writing,[4] Binance, OKX, and Bybit, now offer copy-trading services.

However, revenue incentives in copy-trading platforms can cause conflicts of interest. Copiers want to find competent leaders, while leaders are incentivized to *appear* profitable, since their monetary

[1] https://www.etoro.com/en-us/.
[2] https://www.zulutrade.com/.
[3] https://ayondo.com/.
[4] https://coinmarketcap.com/rankings/exchanges/derivatives/

rewards increase with the number of copiers. In addition, the platform itself profits from trading commissions, which may lead it to prioritize trading volume over user profits. This revenue structure can lead to the use of *manipulative design patterns* (also known as "*dark patterns*") [30, 38, 48, 57, 58]—design features adopted to covertly raise *user engagement* [20] (i.e., here, getting users to trade more than they originally planned). A particularly prominent manipulative design pattern in copy-trading platforms is *gamification* [21, 30]. Specifically, copy-trading platforms advertise top portfolios on their main (landing) pages with leading phrases like "most liked" and "most profitable." One of the platforms we study adorns top portfolios with crown icons. Moreover, many platforms hold trading competitions between users, and offer bonuses to users who trade more. Among gamification features, *leaderboards* are common to all cryptocurrency copy-trading platforms. These leaderboards sort leader portfolios based on certain performance metrics. High-ranking portfolios are prominently featured, while low-ranking portfolios are virtually invisible to copy traders. This can create perverse incentives: instead of trying to maximize the performance of their portfolio, leaders may try to get as high a leaderboard rank as possible. This is particularly problematic if the correlation between a portfolio's actual financial returns and its leaderboard ranking is weak.

Prior literature on search engine result pages (SERP) unfortunately suggests strategies optimizing for leaderboard placement are likely to yield success. Guan and Cutrell [32] show that SERP sorting order matters significantly. Pages that rank higher are more likely to be found than those with a lower rank, which are virtually invisible. More recently, Trielli and Diakopoulos [64] and Gleason et al. [29] confirm that top-ranked items dominate clicks, and also show that SERP design affects subsequent browsing behavior. These phenomena are not limited to information searches. For product searches (i.e., those that ultimately involve a payment), Edelman and Lai [23] demonstrate that the highlighted area for paid listings in Google's flight search influences user choices. In short, these prior studies hint that portfolios ranked high on a leaderboard should attract more copiers, regardless of actual financial performance.

The fundamental question we attempt to answer in this work is whether current market designs adopted by copy trading platforms truly benefit users—both leaders and copiers. While design patterns, particularly leaderboards, may significantly impact user behavior on many online platforms, the monetary stake involved in portfolio choice is particularly significant here: the average copier entrusts USD 500–2 000 to their leaders, and some greatly exceed these amount. Furthermore, financial literature suggests choosing portfolios based on past performance records, which leaderboards are based on, carries high risk [19, 22, 49].

To the best of our knowledge, however, the extent to which user interface (here, leaderboard) design features influence user choice when potentially large amounts of money are at stake remains an unexplored question. UI design effects are extensively studied in online shopping [38, 46], social media [57], privacy protection [2, 3, 67], but there is a notable lack of analysis for online financial services, where the monetary stake is much more consequent than in these other environments. The paucity of work in the area may be due to the relative recency of online financial services. However, they are currently experiencing a rapid rise: a study shows that 17% of US adults, particularly young adults (e.g., 41% of young men), have participated in cryptocurrency trading, which is primarily offered via online platforms and mobile apps [26]. This is an impressive percentage considering that modern cryptocurrencies appeared in 2008, and were virtually unknown to the mainstream until 2011.

To fill this gap in the literature, we attempt to measure the impact of UI design patterns on online financial services, specifically by answering the following research questions:

- **RQ1** Does (cryptocurrency) copy-trading platform website design, specifically the ranking order of leader portfolios, influence copiers' trading choices?
- **RQ2** Does current platform design help copy-traders realize profits and "beat the market"?
- **RQ3** Are there systematic dangers inherent to the current designs of (cryptocurrency) copy-trading markets? If so, which measures can help users recognize risks and evaluate the merits of copy trading?

Our research can also contribute to addressing financial regulator concerns. Online marketplaces' use of "digital engagement practices" (DEPs)—the term regulators have recently started using to refer to design features chosen for attracting users, including leaderboards—are receiving increased attention as online trading grows and starts to foster new trading behaviors, such as trading activism as exemplified by the GameStop frenzy [27]. More precisely, the U.S. Securities and Exchange Commission (SEC) released a request for comments (RFC) on the use of DEPs in 2021 [60]. The UK Financial Conduct Authority (FCA) also recently published an analysis that suggests that online platforms employ design practices that may have an adverse effect on consumers, and called for further study [33].

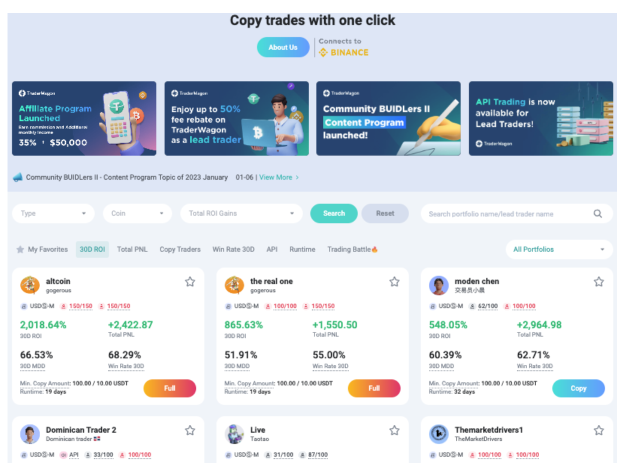



**Figure 1: TraderWagon landing page (Jan. 2023). This landing page prominently advertises one can "copy trades with one click," and lists a number of leader portfolios, ranked, here, by 30-day return on investment.**

To answer these questions, we analyze two major cryptocurrency derivatives copy-trading platforms: TraderWagon[5] and Bybit.[6] Both platforms prominently feature a leaderboard that ranks published portfolios—Figure 1 shows TraderWagon's (old) landing page as an example. It prominently advertises that one can "copy trades with one click," and presents a list of "top" portfolios (ranked here by 30-day return-on-investment) that users may want to copy. These designs seemingly aim to reduce copiers' friction and help them get started with copy trading.

We find that portfolio popularity is highly correlated with how the platform ranks them, rather than their actual performance. Even though both platforms use different ranking algorithms, copiers predominantly follow whatever ranking scheme the platform suggests. Serendipitously, TraderWagon slightly modified its front page during our study and substituted return-on-investment (ROI)-based rankings for an assortment of short lists each ranking a different metric. We show, through a regression analysis, that this coincides with statistically significant decreases in the number of copiers explained by the ROI-based ranking (**RQ1**).

Neither of the ranking choices is directly correlated with long-term performance. In Bybit's case, rankings reflect leader popularity more than actual performance, and are poorly correlated with future returns. In TraderWagon, rankings over-emphasize recent past performance of a specific portfolio, rather than the consistent excellence of a given trader (**RQ2**). Crucially, in both cases, leaders do not have to bear large financial risks to climb up the rankings and reap the benefits of having many copiers – even if for a short time. This means leaders can easily abuse leaderboards to increase profits made from copiers.

Furthermore, copy-trading platforms and the exchanges where trading is taking place are incentivized to foster much copy-trading activity as possible, since this drives trading volumes and ultimately platform profits, which leads to undesirable copy-trading platform designs (**RQ3**). We discuss potential solutions to fix these misaligned incentives.

## 2 RELATED WORK AND BACKGROUND

This section discusses the background on copy trading, and highlights some of the challenges users face when investing in cryptocurrencies. We also discuss more extensively prior work on the influence of UI design patterns, especially manipulative designs.

*Copy-trading complexities.* Even though there is no direct money transfer between copiers (or "followers") and leaders (also known as "signal providers") who publish their portfolios, most literature discusses copy trading as a form of delegated portfolio management [19, 49, 54].

Delegated portfolio management involves various activities that differ in accountability. At one end of the spectrum, investment funds and money managers are legally required to disclose their performance so that investors can make informed decisions. While the obligation is demanding, trustworthy information helps competitive firms attract customers. On the other end, traders with a large social media following, known as "finfluencers," have no accountability and may even make public statements that conflict with their actual trading positions [39]. As a result, followers may want more assurance to properly judge of the value of the advice they are receiving.

Copy-trading services (including those for traditional financial assets) were launched to let novice traders leverage the knowledge of more experienced traders, while providing reputational checks to ensure these novice traders follow sound advice. More precisely, copy-trading platforms attempt to provide a reliable delegated portfolio management system in two ways. First, they make signal providers accountable by disclosing their investment performance. Second, they also make it easy for signal providers to discuss their outlooks and investment strategies.

However, while such disclosures should help copiers exercise due diligence, Huddart [35] claims that it is difficult to distinguish whether signal providers' past performance is attributable to their trading skills or to exogenous factors like mere luck. On the contrary, Huddart argues that, because copy-trading platforms have very low barriers to entry (i.e., virtually anybody can become a signal provider), they motivate traders to take risky positions to differentiate themselves from the rest of the pack. Equally concerning, Dorflietner et al. [22] show that simply following high-performance portfolios, which are often prominently featured on copy-trading platforms, can lead to losses. Doering et al. [19] and Neumann [49] explain this by showing that signal provider investment returns display non-normal distributions, which yield systematic risks of rare but large losses for followers. Instead, they claim that copiers should choose leaders using risk-adjusted performance metrics.

As we will demonstrate, these findings may be misaligned with the incentives of the copy-trading platforms themselves. Indeed, copy-trading platforms make money from trading volumes—it does not matter who wins and who loses (and how much they win/lose), as long as they trade. Therefore, these platforms may prefer to adopt features that increase trading volume over any other metric, including customer success.

*Leader compensation mechanisms.* How leaders are compensated is a crucial factor in the success of copy-trading platforms. Indeed, the competitiveness of these platforms depends on the quality of leaders, and capable leaders will choose the platform that they feel fairly rewards their contributions to the platform success. However, there is a risk of moral hazard if the compensation scheme incentivizes leaders to engage in deceptive activities or excess risk-taking. Therefore, it is essential that copy-trading platforms adopt compensation schemes that strike a balance between attracting leaders and maintaining market integrity.

Different copy-trading platforms, including the platforms we study, use different compensation mechanisms to incentivize signal providers to publish their portfolios. *Profit-based* models, where signal providers receive a share of followers' profit, are common. Crucially, signal providers who take erroneous positions generally do *not* share in their followers' losses. As a result, while profit-based models can help attract talented signal providers, they can motivate leaders to take excessive risks since their profits are multiplied when they win, while their losses are limited to their own bids [14]. Another compensation model is *volume-based*, where signal providers receive revenue proportional to the trading volume copying their portfolios. In this model, compensation is a function of

[5]https://www.traderwagon.com/.
[6]https://www.bybit.com/copyTrade/.

trading volume rather than profit, which in theory should mitigate excess risk-taking by signal providers. However, Chevalier et al. [15] and Sirri et al. [61] show that, even here, signal providers have the motivation to take risky positions. In short, finding a compensation model that fosters sound incentives for leaders to trade without impairing market integrity remains an open problem.

*Cryptocurrency copy trading.* In the past few years, cryptocurrency trading markets started integrating copy trading services into their online platforms. Tellingly, the top three cryptocurrency exchanges at the time of writing,[4] Binance, OKX, and Bybit, offer copy trading services. The main motivation is that cryptocurrencies are complex, "high-tech," and thus require a high level of expertise to invest in them. At the same time, their rapid appreciation has led to fortunes being made almost overnight, sparking a "fear of missing out" (FOMO) in those who did not invest [1].

More precisely, cryptocurrencies are among the most volatile class of financial assets, and are thus predominantly recognized as highly speculative investments [8]. There is no broad consensus about their fundamental underlying value, if any, despite myriads of theoretical [9, 16, 52, 53, 59, 62] and empirical [43] analyses. As such, forecasting their rise or fall is a notoriously treacherous exercise; in addition, contrary to many traditional financial markets, cryptocurrency markets are open 24/7, 365 days a year, which makes them particularly difficult to constantly monitor.

Despite these difficulties, cryptocurrencies have become popular enough that *derivative* products, such as "perpetual futures" [4, 5], are now being offered. According to Kawai et al. [40], a leading crypto-derivatives exchange had more than eight million users in 2021. An important feature of these derivative exchanges is that investors can engage in *leveraged trading* (simply put, trading with a profit or loss multiplier). While leveraged trading offers a chance for small investors to make significant profits, the risk they bear also increases proportionally. The levels of leverage are far higher than those allowed in traditional financial markets, and make it even more critical to pick the right bets to profit. More often than not, though, they spell disaster for retail-level investors [63]. It is therefore unsurprising that investors—especially novices—look for expert insights, thereby leading copy-trading platforms to flourish.

*Research on cryptocurrency use.* In recent years, numerous studies have explored the usability and user experience of cryptocurrencies, including in non-investment contexts [36, 44]. Sas et al. [56] show that cryptocurrencies' novel features, e.g., decentralization and independence from trusted third parties, contribute to broad adoption, and Elsden et al. [24] generate a typology of challenges cryptocurrencies pose, focusing on their design choices. The UI of cryptocurrency-related services has been extensively studied: Voskobojnikov et al. [68] show user risks inherent to the design choices in wallet software, and Krafft et al. [42] argue that the UI design of spot exchanges can magnify peer-traders' influence on investment behaviors.

Johani et al. [37] evidence that cryptocurrency price volatility positively correlates with hype-driven posts in online forums, while tech-focused discussions tend to lead to lower price volatility. This result echoes Gao et al. [28]'s finding that cryptocurrency holders comprise both short-term investors and users believing in future success.

These prior studies both show that UI design is critical, and that investors are susceptible to their peers. Our work advances these efforts further by examining the impact of manipulative design patterns embedded in emerging new services, and the potential new risks they breed.

*Influence of design patterns.* As competition between various online services—including financial services—became increasingly fierce, some of these online services started to adopt "manipulative design patterns." Bringnull first compiled a taxonomy of such design patterns [11], and Grey et al. re-classified manipulative design patterns into five categories [30]. The common feature of these patterns is that they exploit our cognitive biases to gain more user engagement [48].

Manipulative design patterns are surprisingly common. Mathur et al. show 1 818 out of 11K shopping sites use manipulative design patterns [46]. Beyond shopping sites, Schaffer et al. show social media use manipulative designs to discourage users from deleting their accounts [57]. Likewise, Netflix reportedly designs its website to make users watch videos longer than they originally planned [58]. Other studies report manipulative designs that nudge users to compromise their privacy [2, 3, 50, 67].

A manipulative design pattern particularly relevant to our study is "gamification," i.e., integrating game-like features [11, 30]. While gamification itself is not necessarily manipulative *per se*, it can be an extremely effective technique to increase user engagement. Service providers implement gamification by offering users rewards (or fame) as they accomplish certain tasks or meet certain goals. Some literature suggests that gamification may facilitate education [21, 30]; the flip side of the coin is that users might be spending unreasonable amounts of time and money. As we will see, copy-trading platforms actively engage in gamification, by advertising various bonus programs and prominently featuring leaderboards—one of the hallmarks of gamification [30]. These features potentially incentivize *leaders* to increase their trading volume to maximize rewards and publicity.

Leaderboards can also negatively affect *copiers*. Recall the TraderWagon example in Figure 1. These pages are, to some extent, similar to top results presented by search engine results pages (SERPs), whose influence has been extensively studied. Studies document that SERP design significantly affects both user browsing behavior and click-through rates [23, 29, 32, 64]. More precisely, the way information is laid out is critical, as Huang et al. [34]'s analysis of mouse movements shows. Novin and Meyers [51] and Azzopardi [6] discuss cognitive biases having a substantial influence on searching behaviors. Epstein et al. [25] even shows, through an experiment with respondents in dozens of countries, that SERP ranking algorithms are capable of influencing election polls. These prior works all evidence the critical impact of information ranking algorithms on users.

While literature documents the use of manipulative designs in various online services and the substantial influence of SERP design, studies about online financial services are notably scarce, possibly due to the relative novelty of these platforms. However, as online financial services are increasingly directly marketed toward individuals [7, 39, 63], studying the impact of design choices in online financial platforms is becoming more important. Our study attempts to provide a first step toward understanding and quantifying the risks inherent to design choices in online financial services, using cryptocurrency copy-trading platforms as a case study. Another potential key contribution of our study is to examine the influence of UI design on user behavior in a high-stake situation. Indeed, although prior research distinctly evidences UI design influence, whether the situation changes (and if so, how, and to which extent), when users face higher stakes (e.g., monetary losses), is a far more challenging question to address. Our analysis of real market data can help us move toward an answer to this question.

## 3 DATASET

We collect investor data from TraderWagon[5] and Bybit,[6] two major copy-trading platforms for "perpetual futures," from Oct. 2022 to Aug. 2023. This section briefly introduces each platform and describes our dataset of users' investment records.

*Ethics of data collection.* Importantly, none of the data we collect—on either platform—contain personal identifiers: trader accounts, in particular, are completely pseudonymous. In addition, we are not correlating multiple sources of data (instead, we use and analyze TraderWagon and Bybit data independently). Therefore, our work, according to our institutional rules, does not qualify as human-subject research, and is thus not subject to IRB review. We are also purposely only using the publicly available API from the sites (as opposed to, e.g., scraping pages), and in doing so, do not violate TraderWagon and Bybit's terms of service.

### 3.1 TraderWagon Data

TraderWagon was launched in Dec. 2021.[7] The primary function of the platform is to match investors willing to publish their portfolios (leaders or signal providers) with those who want to copy them (copiers or followers), in exchange for potential additional profit. Through a partnership with Binance Futures, the largest online cryptocurrency derivatives market at the time of writing,[4] orders from TraderWagon investors are executed on the Binance Futures market (see Appendix A for details). TraderWagon announced that its service would be migrated to Binance in late Dec. 2023,[8] and Binance now hosts a copy-trading platform similar to TraderWagon.[9]

To assist in matching leaders to copiers, TraderWagon provides a ranking, or "leaderboard," of published portfolios sorted by several investment-performance metrics. As shown in Figure 2, leaders can have multiple portfolios, and copiers select portfolios, rather than individuals. This leaderboard was originally on the site's front page, as shown in Figure 1. (We will discuss later updates to the interface that took place during the course of our study, but they can be ignored for the moment.) These performance metrics include profit and loss (PnL, the total amount of money made or lost in a given interval; in the case of Figure 1, since the portfolio was published), return on investment (ROI, that is, the percentage of money made or lost compared to the initial investment, over a given interval of time; in the case of Figure 1, 30 days); among a host of other metrics we discuss in Appendix A.

[7]https://www.facebook.com/photo/?fbid=202413802285898.
[8]https://traderwagon.zendesk.com/hc/en-us/articles/25580027833753.
[9]https://www.binance.com/en/copy-trading

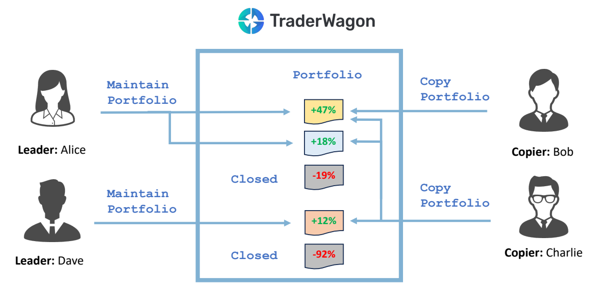



**Figure 2: Portfolio publication and selection on Traderwagon. Leaders (Alice and Dave) publish, maintain, and close portfolio(s). Copiers (Bob and Charlie) select portfolio(s) to copy. The investment performance is calculated for each portfolio.**

TraderWagon also features a number of reward programs. In particular, a referral program allows users to earn a continuous stream of income from their referrals' trading fees.[10] Users who have been referred by others can earn rewards simply by making copy trades.[11] Along the same lines, TraderWagon also has an affiliate program that compensates users for growing their social media following.[12] Last, TraderWagon hosts trading competitions, where participants can earn rewards by achieving high scores according to certain performance metric(s).[13] All of these programs appear to be designed to increase user engagement.

TraderWagon uses *profit-based* and conditional *volume-based* compensations schemes for signal providers/leaders.[14] If a copier closes positions with a positive realized PnL, the associated leader receives 10% of the profit the copier made as their share for portfolio publication. Moreover, if the weekly PnL of the copier is positive, the leader additionally receives 10% of the transaction fee paid for copying their portfolio.

Copiers, broadly speaking, have two options for copying a leader portfolio:[15] *fixed-ratio* or *fixed-amount*. With fixed-ratio, copiers mirror the portfolio investment ratios across positions. For instance, if the leader puts USD 100 in their portfolio margin account – that is, they send USD 100 to the platform for trading, and of these, use USD 10 on asset A, and USD 20 on asset B (the rest is unused), the copier will use 10% of their own investment toward asset A and 20% on asset B, *regardless of the amount of money* the copier has in their own margin account.[16] For instance, if the copier has USD 10 000 in their margin, fixed-ratio will lead them to acquire USD 1 000 worth of asset A, and USD 2 000 worth of asset B. With fixed-amount,

[10]https://www.traderwagon.com/en/activity/referral
[11]https://traderwagon.zendesk.com/hc/en-us/articles/23347449396633-Copy-Trade-on-TraderWagon-Mini-Program-Share-3-000-
[12]https://traderwagon.zendesk.com/hc/en-us/articles/9968168524057-TraderWagon-Affiliate-Program
[13]https://traderwagon.zendesk.com/hc/en-us/articles/22355450095385-Autumn-Trading-Festival-Battle
[14]https://traderwagon.zendesk.com/hc/en-us/articles/9991481873817-Lead-Trader-Benefit-Update-2022-08-01-
[15]https://traderwagon.zendesk.com/hc/en-us/articles/9996958558489-How-to-copy-trade-on-TraderWagon-
[16]If the position size is below (resp. above) the minimum (resp. maximum) amount for copying, the platform adjusts the amount to be compliant with the threshold (https://traderwagon.zendesk.com/hc/en-us/articles/9803988508185-Copy-Rules-on-TraderWagon).

in short, copiers set total and per-asset amounts when they start copying a portfolio (see Appendix A for the details).

TraderWagon sets a maximum number of followers (i.e., a quota) to portfolios separately for each copying mode, ranging from 50 to 200. The maximum quota is determined by the portfolio margin size and the number of copiers.[17] Leaders may close existing portfolios and open new ones at any time.

*Data collected.* We collect data from TraderWagon's publicly available API from Oct. 26, 2022, to Aug. 31, 2023. The API provides metadata and numeric values about performance metrics (e.g., PnL and ROI) of leaders' portfolios, reportedly updated once every ten minutes. We also collect data about ongoing and closed positions for each portfolio, underlying cryptocurrencies involved (e.g., BTC/USDT), position amount and side (long or short). In addition, closed position data includes its realized PnL for both the leader and their copiers. We collected portfolio data every twelve hours and position data every seven days, until Feb. 4, 2023. We then gradually shifted to shorter data collection intervals to increase data resolution. We collected portfolio data every two hours until Feb. 27, 2023, and every ten minutes thereafter. We collected position data every day after Feb. 4, 2023.

*Publication rules.* On TraderWagon, a single leader can publish up to six portfolios whose performance metrics are independently calculated.[18] As such, holding a top-tier portfolio is not a guarantee of a leader's overall performance: they may simultaneously have negative-profit and top-tier portfolios. For instance, in Figure 2, Dave has a portfolio up 12% that is still open, but also recently closed a portfolio which was down 92%. In addition, leaders can close losing portfolios and open new ones at their discretion, which allows them to establish a better performance history by rapidly clearing underperforming portfolios.

There is practical evidence that some leaders adopt this very strategy. Figure 3 shows a specific leader history, namely their

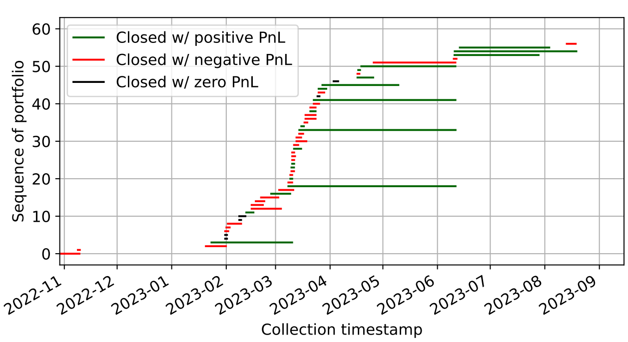
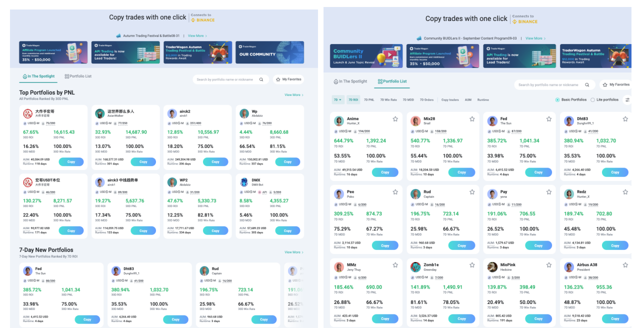



**Figure 3: Portfolio publication and closure records of a leader. The fourth portfolio from the bottom (in green) was listed on the front page in Feb. 2023. However, most of this leader's portfolios closed quickly with losses thereafter.**

record of publishing and closing portfolios.[19] The fourth portfolio they opened (lowest green line in Figure 3) was successful, and ended up being listed on the top page of TraderWagon in Feb. 2023. However, many of their subsequent portfolio choices ended up being closed with negative profits within a few days of their creation; this leader only managed a small number of portfolios for months. In short, they try multiple investment strategies almost simultaneously, and only keep successful ones. This strongly questions the legitimacy of the portfolio leaderboard as an indicator of overall leader performance.




**(a) Landing page after website update** **(b) Leaderboard page after website update**

**Figure 4: TraderWagon interface update**

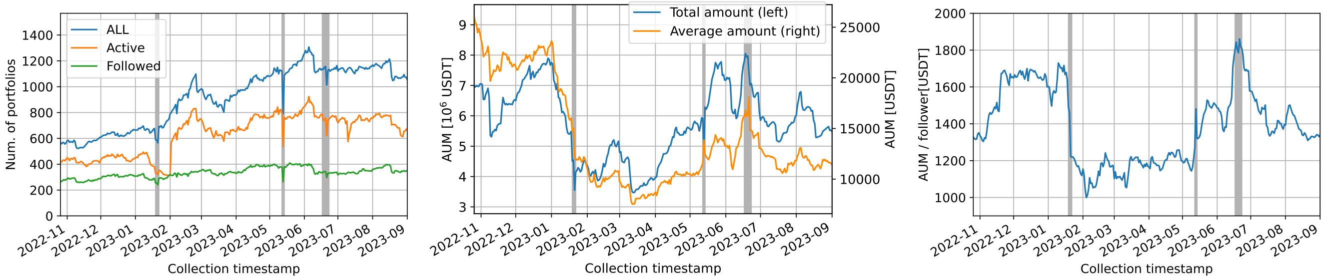
*Website design update.* In mid-March 2023, TraderWagon abruptly changed the design of its website. As shown in Figure 1, before the update, TraderWagon's landing page listed up to 18 top portfolios ranked by 30-day ROI. After the update, as shown in Figure 4a, the top page started displaying only four to eight portfolios instead, ranked using several metrics. The leaderboard also changed (Figure 4b), listing now 20 portfolios, and ordered by 7-day ROI. Switching from 30-day ROI to 7-day ROI does not have a major impact: 44.0% of the top-20 portfolios using the 7-day ROI ranking are also in the top-20 using the 30-day ROI ranking.

In addition, TraderWagon switched from showing lifetime PnLs to showing 7-day, 30-day, and 90-day PnL after the update. The latter is a close approximation of the lifetime PnL, as portfolios are typically shorter-lived (median: 2.9 days, average: 16.1 days). Except for the different time interval, we did not observe any changes in the calculation of performance metrics. Therefore, this update primarily focused on the website UI design.

Finally, TraderWagon started to allow Binance Futures investors to publish portfolios without registering to TraderWagon in late Feb. 2023.[20] However, we exclude these portfolios since they are listed separately from those opened by TraderWagon-registered leaders, and usually only have a few copiers.

*Descriptive statistics.* Figure 5 shows the number of portfolios and the amount of money staked by followers. Specifically, Fig. 5a shows

[17]https://traderwagon.zendesk.com/hc/en-us/articles/10550738425497-TraderWagon-Copier-Slots-Adjustment-Rule
[18]https://traderwagon.zendesk.com/hc/en-us/articles/9974805106713-Lead-Trader-Introduction.
[19]Due to the sparser collection interval, some very short-lived portfolios closed before Feb.4 2023 are omitted. However, their PnLs show the same trend as portfolios in the figure.
[20]https://traderwagon.zendesk.com/hc/en-us/articles/13003877909657-What-is-Binance-Leaderboard-Lite-Lead-Trading.




**(a) Number of portfolios**

**(b) Total and average AUM per followed portfolio**

**(c) Average amount of money staked by copiers**

**Figure 5: Descriptive statistics for TraderWagon investors. Light gray-shaded areas denote partial temporary outages of our collection infrastructure.**

the number of portfolios, where active portfolios denote those with non-zero PnL values (i.e., taking positions) in the past seven days; Fig. 5b shows the total copiers' assets under management (AUM) in TraderWagon and the average AUM per portfolio, where average AUM is calculated from the total copy amount divided by the number of followed portfolios; and Fig. 5c shows the average amount of money a copier entrusts to a portfolio.

The total number of available and active portfolios (Fig. 5a) increases over time. On the other hand, the number of portfolios with followers is roughly stable, indicating that the total number of available options does not appear to greatly influence copiers' choices. The total amount of money entrusted to leaders (Fig. 5b) is 3–8 million USD in our observation period. This is orders of magnitude smaller than the amount of money allegedly deposited to Binance, which is in the billions of US dollars [66]. However, more interestingly, this means that, on average, roughly USD 10 000 are entrusted to each active published leader portfolio, even though there is *absolutely no performance or qualification requirements* to become a leader. Each copier, on average, invests between USD 1 000–2 000 with leaders (Fig. 5c). In short, copiers invest non-negligible amounts of money into leaders, who have not been subject to any strict vetting process.

## 3.2 Bybit Data

Bybit is a major online cryptocurrency exchange with the second-largest cryptocurrency trading platform at the time of writing.[4] The exchange was launched in 2018, and started to host a copy-trading platform in April 2022,[21] which was awarded an iF design award in 2023 for user experience (UX).[22] Similar to TraderWagon, Bybit sorts published portfolios on a leaderboard based on PnLs, ROIs, and other performance-related metrics; and holds campaigns and trading competitions to attract more investors to the platform. Figure 6 shows example screenshots of Bybit. The top-page design (Figure 6a) is very similar to TraderWagon after the update, but the leaderboard page (Figure 6b) uses the aggregated 7-day PnL over all copiers. The landing page notably uses bright colors and crowns on the top three portfolios' icons. Bybit also periodically advertises trading campaigns, in particular, the "World Series of Trading (WSOT, Figure 6c).[23] Bybit provides bonuses to highly ranked leaders and copiers participating in the WSOT.

Bybit employs a *profit-based* compensation scheme. Leaders gain between 10% and 15% of their copiers' profits depending on a trader level assigned by the platform. New leaders start at the lowest level, "Cadet," and receive 10% of their copiers' profits. Leaders can climb up levels by depositing funds and consistently generating profits.[24] Leaders at the highest level, "Gold," receive 15%.

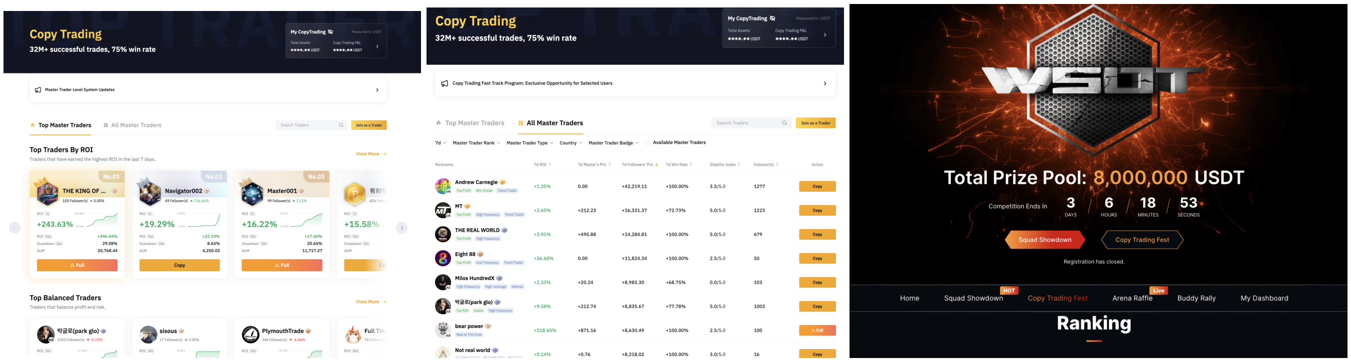
Likewise, each leader is limited to a maximum number of copiers, determined by the leader's level: Cadets can have at most 100 copiers, while Gold can have 2 000. As an interesting exception, WSOT participants are allowed to have 2 000 copiers regardless of their level. Copiers have two options for mirroring portfolios: (1) a mode similar to *fixed-ratio* mode in TraderWagon and (2) setting copy parameters by themselves.[25] Bybit recommends the first choice to beginners.

*Data collected.* We collect data from Bybit's publicly available API from Feb. 18, 2023 to Aug. 31, 2023. The API provides leader metadata and performance metrics, such as PnL and ROI, as well as rankings derived from these metrics for 7-, 30-, and 90-day intervals. The API also gives the number of followers and their associated profit from copying positions for each published portfolio. We collect these data every two hours throughout our observation period.

*Publication rules.* Until Mar. 2023, on Bybit, leaders were allowed to publish only a single portfolio. However, in Apr. 2023, Bybit announced that it would, from then on, allow users to create "sub-accounts," distinct from their main accounts for copy trading.[26] Leaders can use these subaccounts to publish more than one portfolio, and/or simultaneously be copiers. The Bybit website and API

[21] https://finance.yahoo.com/news/bybit-launch-copy-trading-084400033.html.
[22] https://ifdesign.com/en/winner-ranking/project/bybit-copytrading/581618.

[23] https://www.bybit.com/en-US/wsot2023/copy-trading-fest/#wsot-navs.
[24] The level assignment follows a rule (https://announcements.bybit.com/en-US/article/copy-trading-3-0-score-more-perks-with-master-trader-level-system-bltb48d31b1e994bb85/). Bybit changed the criteria (https://www.bybit.com/en-US/promo/global/master-trader-level) on Aug. 26, 2023.
[25] https://learn.bybit.com/copy-trading/what-is-bybit-smart-copy-mode/
[26] https://announcements.bybit.com/en-US/article/copy-trading-subaccounts-now-supported-improved-copy-stop-loss-bltfeb873447aec27ae/.




(a) Landing page (b) Leaderboard page (c) WSOT campaign page

**Figure 6: Screenshot examples of Bybit web interface.**

do not provide information to immediately link a specific portfolio (and the subaccount involved) with a main account.

*Descriptive statistics.* Figure 7 shows the number of published portfolios, the total and average AUMs, and the average amount of money entrusted by a copier, where definitions for statistics are the same as TraderWagon.

Fig. 7a shows that the number of published portfolios steadily increases over time, but number of followed portfolios remains roughly constant at 2 000. This mirrors what we saw in TraderWagon: an increased number of leader options does not mean that these options are particularly popular with copiers. In contrast, a clear difference between TraderWagon and Bybit is the ratio of active portfolios to the total number of portfolios: more than 50% for TraderWagon, but below 20% for Bybit, where a majority of portfolios are thus dormant. This can be explained by differences in portfolio publication rules. As we have seen, leaders in TraderWagon have a strong incentive to immediately close unprofitable portfolios and create new ones, while – at least until Apr. 2023 – Bybit restricted each leader to a single portfolio. Fig. 7b shows that, similar to TraderWagon, the average AUM in Bybit is in the order of USD 10 000. However, Fig. 7c shows that copiers individually invest less money (around USD 500) than in TraderWagon; the average amount is steadily increasing over time.

## 4 METHODS

To analyze the influence of the leaderboard on how copiers select portfolios, we employ a quantile regression (QR) of *portfolio popularity* for TraderWagon data. This section introduces this quantile regression.

For a given portfolio, we formally define *portfolio popularity* as the ratio between the number of copiers and the maximum number of copiers allowed for that portfolio. A popularity of 1 denotes an extremely popular portfolio (which cannot afford more subscribers), whereas a popularity of 0 denotes a portfolio with no copiers at all. Using this normalized metric eschews issues stemming from different tiers of leaders being allowed different maximum number of copiers (see Section 3 for details). The justification for using portfolio popularity is described in Appendix C.

### 4.1 Quantile Regression

Instead of following a normal distribution, the conditional distribution of portfolio popularity conditioned on explanatory variables (e.g., ROI and performance metrics-based rank) is highly skewed to lower values. As a result, a simple ordinary least square (OLS) regression could miss important effects of explanatory variables.

In contrast, a quantile regression (QR, [41]) can estimate coefficients without any normality assumptions on the underlying distributions. Hence, QR is robust to the skewness and outliers that are evident in our dataset, which makes it a desirable technique for us. An added benefit of QR is that we can estimate the coefficients for arbitrary quantiles: we can separately consider the impact of explanatory variables on portfolios with small (i.e., low quantile) and large (high quantile) portfolio popularity.

QR estimates the conditional quantiles of a dependent variable ($y$) conditional on explanatory variables ($x$) [13, 17],

$$Q_\theta(y_i|x_i) = x_i^T \beta_\theta ,$$

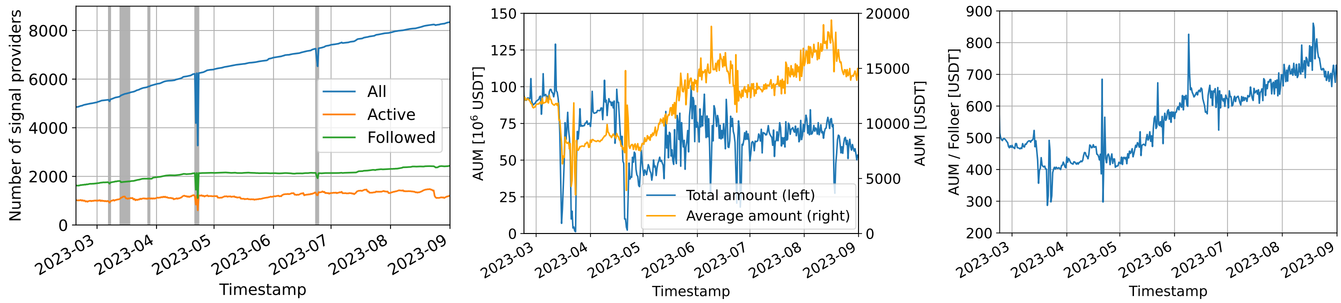
where $i$ denote the index for observations ($i = 1, \ldots, N$) and $x_i$ is a $K \times 1$ vector showing a set of observed explanatory variables. $Q_\theta$ denotes the expected $\theta$-th quantile of $\{y\}_{i=1\ldots N}$ given $\{x\}_{i=1\ldots N}$.

We can analyze which explanatory variable has the most influence on portfolio popularity for different quantiles, by performing multiple QR analyses with different $\theta$.

### 4.2 Model construction

TraderWagon features between 600–1,200 portfolios in our observation period (see Figure 5). However, more than half of these portfolios are dormant with zero or negative ROI, so they will not be attractive to copiers; in fact, they likely will be buried in the interface, and potential copiers would have to make significant effort to find them. Hence, we hypothesize that only a few, if any, copiers will consider negative-PnL portfolios. Conservatively, we assume that most copiers will consider the top 100 ranked portfolios.

*Model variables.* We build a model to infer the influence of performance metrics and interface design on portfolio popularity. We denote the maximum number of copiers allowed for portfolio $i$ at




**(a) Number of portfolios** **(b) Total and average AUM per followed portfolio** **(c) Average amount of money staked by copiers**

**Figure 7: Descriptive statistics for Bybit investors. Light gray-shaded areas denote partial temporary outages of our collection infrastructure.**

time $t$ on TraderWagon by $N^{\max}_{i,t}$. $N^{\max}_{i,t}$ ranges from 150 to 400.[27] Let $N_{i,t}$ be the number of copiers of portfolio $i$. We can then formally define portfolio popularity for portfolio $i$ at time $t$ as:

$$r_{i,t} = N_{i,t}/N^{Max}_{i,t} \ .$$

We next turn to explanatory variables. We first consider the deviation at time $t$ in 30-day ROI for portfolio $i$ compared to the average ROI over all top 100 portfolios:

$$\widehat{ROI}_{i,t} \equiv ROI_{i,t} - Avg_i\left(ROI_{i,t}\right) \ .$$

Using the deviation from the average, rather than an absolute value, allows us to offset the difference in overall performance across timeslices.

We also consider the (logarithmic) time elapsed from the time portfolio $i$ was opened measured in the unit of days

$$Age_{i,t} \equiv \log(t - T^{launch}_{i,t}) \ ,$$

to help us measure the influence of being exposed to copiers for a longer (resp. shorter) period.

Next, we elaborate on the variable representing the effect of platform design. We primarily want to measure the influence of being among the highest portfolios ranked by ROI, which is used to populate the TraderWagon leaderboard. As discussed in Sec. 3, 18 portfolios were listed on the leaderboard page before the Mar. 16, 2023 update, and 20 thereafter. We thus define an indicator variable:

$$I^{Top}_{i,t} = \begin{cases} 1 & \text{if rank of } i\text{-th portfolio is within top 18} \\ & \text{in 30-day ROI for } t < 3/16/2023, \\ 1 & \text{if rank of } i\text{-th portfolio is within top 20} \\ & \text{in 30-day ROI for } t \geq 3/16/2023, \\ 0 & \text{otherwise.} \end{cases}$$

To remove potential confounding factors, we also consider an indicator variable denoting life-long PnL-based ranking, $I^{PnL}_{i,t}$.[28] This metric is available to users and can be used to rank portfolios, but is *not* the default used for the leaderboard. By contrasting its influence with $I^{Top}_{i,t}$, we can tease out the impact of interface defaults.

$$I^{PnL}_{i,t} = \begin{cases} 1 & \text{if the rank of } i\text{-th portfolio is within top 18} \\ & \text{in lifetime PnL for } t < 3/16/2023, \\ 1 & \text{if the rank of } i\text{-th portfolio is within top 20} \\ & \text{in 90-day PnL for } t \geq 3/16/2023, \\ 0 & \text{otherwise.} \end{cases}$$

Finally, we consider another indicator variable capturing the fact that a portfolio was featured in the leaderboard in the past, even if they are not anymore:

$$I^{Rem}_{i,t} = \begin{cases} 1 & i\text{-th portfolio was on the first page of 30-day ROI-based} \\ & \text{ranking at some time } \tau < t, \text{ but } \textbf{is not} \text{ on the page at } t, \\ 0 & \text{otherwise.} \end{cases}$$

$I^{Rem}_{i,t}$ allows us to differentiate between consistently low-ranking portfolios and those which went down.

We take the twelve-hour average for observations after Feb. 4, 2023, and then consider indicator variables for the average to equate the number of observations per time period. We confirmed that the correlations between explanatory variables are not strong enough to bias our regression analysis. (See Appendix B for details.)

*QR Models.* To summarize, our full-fledged regression model for portfolio popularity is given by

$$r_{i,t} = c_\theta + \beta^1_\theta \widehat{ROI_{i,t}} + \beta^2_\theta Age_{i,t} + \beta^3_\theta I^{Top}_{i,t} + \beta^4_\theta I^{PnL}_{i,t} + \beta^5_\theta I^{Rem}_{i,t} + u_{\theta,i,t} \ , \quad (1)$$

where $u_{\theta,i,t}$ is the error term. Equivalently, $Q_\theta(r_{i,t}) = c_\theta + \beta^1_\theta \widehat{ROI_{i,t}} + \beta^2_\theta Age_{i,t} + \beta^3_\theta I^{Top}_{i,t} + \beta^4_\theta I^{PnL}_{i,t} + \beta^5_\theta I^{Rem}_{i,t}$.

To see the dependence of portfolio popularity's change over time, we also consider the regression model for its first difference, $\Delta r_{i,t} \equiv r_{i,t} - r_{i,t-1}$,

$$\Delta r_{i,t} = \widetilde{c}_\theta + \widetilde{\beta}^1_\theta \Delta\widehat{ROI}_{i,t} + \widetilde{\beta}^2_\theta I^{Top}_{i,t} + \widetilde{\beta}^3_\theta I^{PnL}_{i,t} + \widetilde{\beta}^4_\theta I^{Rem}_{i,t} + \widetilde{u}_{\theta,i,t} \ , \quad (2)$$

where $\Delta\widehat{ROI}_{i,t}$ and $\widetilde{u}_{\theta,i,t}$ are the first difference of the adjusted-ROI, $\Delta\widehat{ROI}_{i,t} \equiv \widehat{ROI}_{i,t} - \widehat{ROI}_{i,t-1}$, and of the error term, respectively.

[27] We observed portfolios with a maximum follower number of 150 only until Nov. 4, 2022. $N^{\max}$ was raised to *at least* 200 subsequently (maximum is 400).

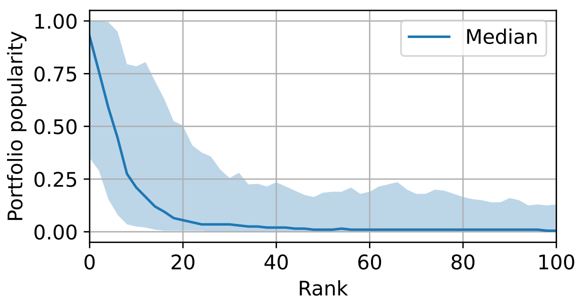
[28] We use the 90-day PnL ranking as a substitute for lifetime PnL after the interface update. 90 days is much longer than the typical portfolio lifetime. See Section 3 for details.

## 5 RESULTS

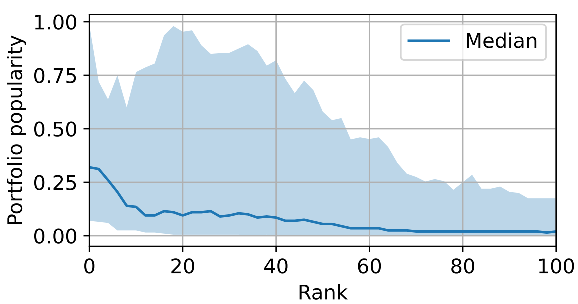
This section first considers the correlation between portfolio popularity and portfolio ranking, before delving into the quantile regression results. Finally, we look into implications of our findings with respect to investment outcomes, i.e., whether the chosen ranking schemes help people maximize profit.

### 5.1 Correlation between publicized portfolios' popularity and rankings

Figure 8 shows how, in TraderWagon, portfolio popularity relates to 30-day ROI- and life-long PnL-based rankings.



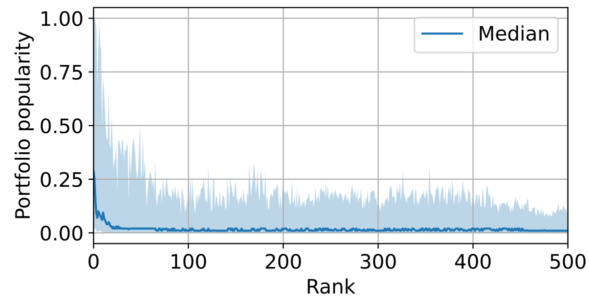

**(a) 30-day ROI ranking**



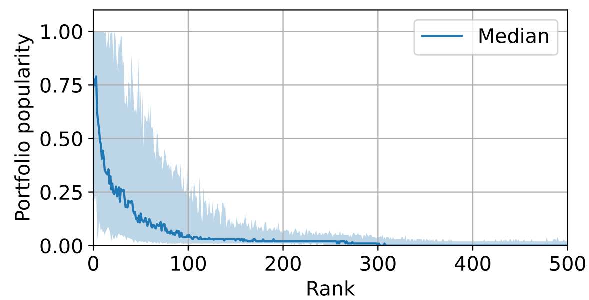

**(b) Life-long PnL ranking**

**Figure 8: Portfolio popularity on TraderWagon as a function of different types of portfolio rankings: 30-day ROI (upper panel), which is the default ranking, and life-long PnL (lower panel). The blue line is the median portfolio popularity (over time) for a given rank. The light blue shaded areas denote the 10th–90th percentiles.**

Figure 8a shows that there appears to be a fairly strong correlation between portfolio popularity and ranking according to the 30-day ROI ranking: higher ranked portfolios are more popular. On the other hand, if we rank portfolios by life-long PnL, the correlation appears to be much more modest; in fact some of the portfolios ranked in the middle of the pack (20–40) appear to be more popular that some of the top ranked ones. These results hint that the choice of TraderWagon to use 30-day ROI ranking as a default to present leaderboard information has a strong impact on popularity. There are two ways we can interpret this result. Copiers may genuinely believe that portfolios with high 30-day ROI are competitive, *out of financial rationality* – that is, they understand how TraderWagon ranks portfolios, and agree with that design choice. The other possibility is that copiers *blindly* choose portfolios shown in the first several pages. Namely, the leaderboard default nudges copiers to select portfolios with high 30-day ROI, even though they may not understand whether it is a good metric or not.




**(a) 30-day ROI ranking**




**(b) 7-day aggregate copiers' PnL ranking**

**Figure 9: Portfolio popularity on Bybit as a function of different types of portfolio rankings: 30-day ROI (upper panel), and 7-day aggregate follower PnL (lower panel); the latter is the default. The blue line is the median portfolio popularity (over time) for a given rank. The light blue shaded areas denote the 10th–90th percentiles.**

To resolve this dilemma, we look at Bybit in Figure 9, where we plot the relationship between 30-day ROI ranking and portfolio popularity (Fig. 9a) and the relationship between the 7-day aggregate follower PnL ranking (i.e., the sum of the PnL of all the followers of a given portfolio) and portfolio popularity (Fig. 9b). [29] The latter reflects what the Bybit leaderboard uses as a default ranking; the former is for comparison with TraderWagon.

Tellingly, in contrast to TraderWagon, portfolio popularity appears to be weakly correlated, if at all, with 30-day ROI ranking. On the other hand, we observe an apparent strong correlation between 7-day aggregate copier PnL ranking and portfolio popularity. This appears to confirm that interface default, rather than the goodness of a specific metric, is crucial to portfolio popularity.

[29] In the calculation, we exclude a small number of portfolios that have ratios larger than 1.0 (2.1% and 2.3% for 30-day ROI and 7-day copiers' PnL ranking, respectively) to avoid noise. Bybit allows portfolios to carry existing copiers when they are demoted in the portfolio level. Hence, the ratio can be temporarily larger than 1.0.

**Table 1: Pearson correlation coefficients between portfolio popularity and portfolio rank based on selected performance metrics. Boldfaced entries represent the interface default for each platform. Blank entries indicate that the platform does not show the metric.**

| | 30-day ROI | Life-long PnL | 30-day Win Rate | 30-day MDD | 7-day agg. copiers PnL |
|---|---|---|---|---|---|
| **TraderWagon** | | | | | |
| *Before update* | **-0.533** | -0.204 | -0.001 | – | – |
| *After update* | **-0.569** | -0.064 | 0.011 | 0.019 | – |
| **Bybit** | -0.251 | -0.574 | -0.259 | – | **-0.647** |

We confirm these insights by computing Pearson correlation coefficients, between the portfolio popularity and ranking according to the different performance metrics used in TraderWagon and Bybit: 30-day ROI, Life-long PnL, 30-day Win-Rate, 30-day maximum drawdown (MDD), and 7-day aggregate followers' PnL. "Win rate" is the percentage of positions that had a positive PnL when they were closed; "maximum drawdown" (MDD) is the maximum percentage difference for a portfolio between its highest PnL and its lowest PnL. We exclude leaders ranked lower than 50 for TraderWagon, and 300 for Bybit, to prevent contamination from low-ranked leaders who are dormant.[30]

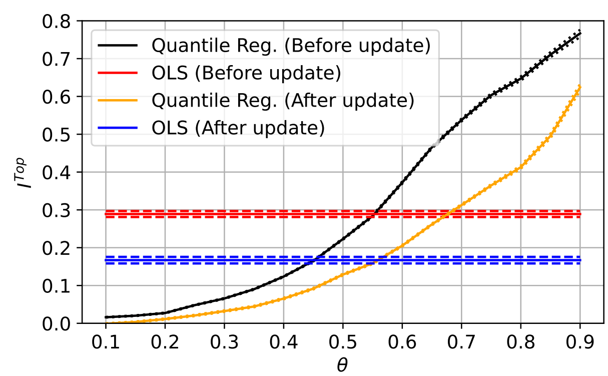
Table 1 summarizes the results. They confirm what we were suspecting from graphical inspection: interface defaults – specifically, default leaderboard rankings – play an outsized role on portfolio popularity. This result also suggests that the leaderboard page influences copiers' choices far more than the front page. TraderWagon and Bybit's landing pages currently show the top-8 portfolios based on the 30-day PnL (TraderWagon) and 7-day ROI (Bybit). There is some overlap with the top-8 portfolios in Table 1: 63.1% of top-8 portfolios in the 90-day PnL ranking on TraderWagon are also in the top-8 of the 30-day PnL ranking; and, 30.5% of the top-8 portfolios in the 7-day ROI ranking on Bybit are also in the top-8 of the 30-day ROI ranking. However, overall, their correlation with portfolio popularity is far smaller than for the portfolios in the respective leaderboard. This indicates that the copiers primarily rely on (at most the first couple of pages of) the leaderboard, even at the detriment of any short list featured on the landing page. One possible explanation is that, to the users, the short lists might look too much like "featured listings," i.e., advertisements, whereas the leaderboard has the appearance of a more objective ranking.

The moderate correlation between life-long PnL and portfolio popularity in Bybit is due to the fact that life-long PnL and 7-day aggregate follower PnL are highly correlated themselves.

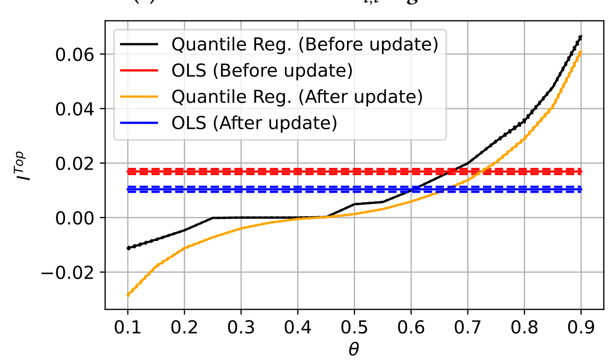
## 5.2 Quantile regression: substantiation of results from correlation coefficients

Table 2 summarizes the results of QR analysis for TraderWagon with the model described in Section 4. We first see that the excess ROI ($\widehat{ROI}$), generally only has little impact on portfolio popularity throughout our observation period. Namely, even if the excess ROI reaches 100% (i.e., $\widehat{ROI} = 1.0$), the number of copiers increases at most by 3–5% before and after the update, respectively. That indicates that ROI, *on its own*, is not a crucial factor for gaining popularity.

On the other hand, if a portfolio ends up in (the first page of) the leaderboard page (i.e., $I^{Top} = 1$), then we see a median increase in popularity of 12.9–22.3%. This is even more true for the 90th percentile: 62.4%–76.7% of popularity are explained by the presence of the portfolio in the leaderboard page. In short, an increased ROI by itself is not enough to gain copiers, but if it leads to the portfolio breaking into the leaderboard, then it pays large dividends.




**(a) $I^{Top}$ coefficients in $r_{i,t}$ regression**




**(b) $I^{Top}$ coefficients in $\Delta r_{i,t}$ regression**

**Figure 10: $I^{Top}$ coefficients, as estimated by quantile regression (QR) and ordinary least square (OLS)-based regression. The dashed lines show 95% confidence intervals.**

Figure 10a generalizes the results from Table 2 by displaying the $I^{Top}$ regression coefficients across all quantile points $\theta$, and

[30]These portfolios have (close to) zero copiers regardless of rank for portfolios below a certain threshold, and are simply adding noise to Pearson correlation coefficients.

**Table 2: Quantile regression results for TraderWagon. We omit the standard errors for the estimated coefficients in quantile regressions since they are very small (typically, in the order of $10^{-4}$ or less due to the large sample size).**

| | Before update ($N$ = 27 879) | | | | | | After update ($N$ = 25 474) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\theta$ | 0.10 | 0.25 | 0.50 | 0.75 | 0.90 | OLS (S.E.) | 0.10 | 0.25 | 0.50 | 0.75 | 0.90 | OLS (S.E.) |
| Regression for $r_{i,t}$ [Eqn. (1)] | | | | | | | | | | | | |
| $c$ | −0.002 | −0.004 | −0.003 | 0.013 | 0.015 | −0.001 (0.004) | 0.012 | 0.027 | 0.051 | 0.066 | 0.061 | 0.055 (0.003) |
| $\boldsymbol{\widehat{ROI}}$ | **0.005** | **0.018** | **0.029** | **0.025** | **0.018** | 0.026 (0.001) | **0.017** | **0.034** | **0.048** | **0.052** | **0.036** | 0.050 (0.001) |
| $Age$ | 0.000 | 0.000 | 0.002 | 0.008 | 0.032 | 0.014 (0.001) | 0.000 | 0.002 | 0.003 | 0.006 | 0.023 | 0.009 (0.001) |
| $\boldsymbol{I^{Top}}$ | **0.016** | **0.048** | **0.223** | **0.603** | **0.767** | 0.289 (0.004) | **−0.001** | **0.021** | **0.129** | **0.365** | **0.624** | 0.167 (0.004) |
| $\boldsymbol{I^{PnL}}$ | **0.035** | **0.077** | **0.151** | **0.203** | **0.347** | 0.167 (0.005) | **0.021** | **0.045** | **0.119** | **0.198** | **0.214** | 0.134 (0.004) |
| $I^{Rem}$ | 0.005 | 0.017 | 0.060 | 0.230 | 0.585 | 0.156 (0.004) | 0.000 | 0.004 | 0.043 | 0.185 | 0.513 | 0.133 (0.003) |
| Pseudo R-sq.† | 0.025 | 0.078 | 0.191 | 0.363 | 0.436 | 0.382 | 0.045 | 0.128 | 0.274 | 0.436 | 0.479 | 0.486 |
| Regression for $\Delta r_{i,t}$ [Eqn. (2)] | | | | | | | | | | | | |
| $\widetilde{c}$ | −0.005 | 0.000 | 0.000 | 0.001 | 0.007 | 0.002 (0.000) | −0.004 | −0.001 | 0.000 | 0.002 | 0.007 | 0.001 (0.000) |
| $\Delta\widehat{ROI}$ | 0.003 | 0.000 | 0.000 | 0.003 | 0.005 | 0.003 (0.000) | 0.009 | 0.004 | 0.002 | 0.007 | 0.010 | 0.015 (0.000) |
| $\boldsymbol{I^{Top}}$ | **−0.011** | **0.000** | **0.005** | **0.028** | **0.067** | 0.017 (0.000) | **−0.028** | **−0.007** | **0.001** | **0.020** | **0.061** | 0.010 (0.000) |
| $I^{PnL}$ | −0.005 | −0.002 | 0.000 | 0.006 | 0.012 | 0.001 (0.001) | −0.004 | −0.001 | 0.001 | 0.005 | 0.011 | 0.002 (0.001) |
| $\boldsymbol{I^{Rem}}$ | **−0.014** | **−0.005** | **0.000** | **0.000** | **0.003** | −0.005 (0.000) | **−0.013** | **−0.004** | **0.000** | **0.000** | **0.002** | −0.004 (0.001) |
| Pseudo R-sq.† | 0.069 | 0.018 | 0.004 | 0.087 | 0.224 | 0.070 | 0.155 | 0.041 | 0.005 | 0.077 | 0.216 | 0.093 |

† R-squared is calculated for OLS results.

confirms the outsized influence of being in the leaderboard page on a portfolio's popularity.

Our regression also tells us that a portfolio's age does not significantly influence its popularity, meaning that simply holding a portfolio does not make it more (or less) popular. Conversely, being among the top-20 portfolios in terms of profits and losses (PnL) does have some impact. PnL is not the default leaderboard ranking in TraderWagon, and its impact on popularity is markedly less than that of $I^{Top}$; but this makes sense because PnL is—to some extent—correlated with ROI (although the correlation could be modest for certain portfolios, as we later explain).

We also look at changes in popularity $\Delta r$. The popularity of portfolios in the 90th percentile increases by 6.1%–6.7% in a half day when a portfolio reaches (the first page of) the leaderboard. Even more tellingly, the adverse effects of dropping off from the first page of the rankings is also evident. The 10-percentile coefficient for $I^{Rem}$ shows that a portfolio will lose 1.3%–1.4% in popularity in a half day after dropping off the leaderboard.

Table 2 shows another interesting effect. Recall that the TraderWagon update essentially moved the leaderboard page to its own page, and started listing slightly different portfolios on the main landing page. The impact of this does appear in our regression analysis: the positive influence of $I^{Top}$ decreased after the interface update (Figure 10). These results suggest that the influence of a portfolio featuring in the top 30-day ROI ranking (i.e., the default for leaderboard in TraderWagon) on its popularity was reduced after the update.

Even so, $I^{Top}$ is still highly influential (especially when considering the 75th-percentile) on portfolio popularity—which goes to show that while copiers follow the default rankings, they primarily trust the leaderboard page, rather than the main landing page.

These results support our hypothesis that leaderboards substantially influence copiers' portfolio choices, suggesting that copiers rely on the perceived credibility of "top-rankers" rather than conducting thorough due diligence by themselves. Unfortunately, this can result in unprofitable investments. Recall the portfolio publication rule on TraderWagon (Section 3): leader can publish a number of portfolios, gaming the leaderboard metrics in the process. As a result, high-performance metrics do not guarantee a leader's trading skills or any financial returns, and in fact, the competitiveness of such portfolios can quickly decline.

## 5.3 TraderWagon: Impact on leader profits

We next turn to leaders. Leader portfolios provide two sources of profit: *direct* profits, that come from the portfolio's PnL; and *indirect* profits, that come from commissions owed by copiers to the leader—namely, 10% of each copiers' profit. The sum of direct and indirect profit yields the *total* profit for a portfolio. We next examine to which extent having a high-ranking portfolio (i.e., present on the leaderboard page) impacts indirect profits.

To do so, we calculate the average ratio between total profit and direct profit:

$$
\begin{aligned}
R_{I,t} &\equiv Avg_{i\in\{I,t\}}\left(\frac{PnL_{Tot,i}}{PnL_{own,i}}\right) \\
&= Avg_{i\in\{I,t\}}\left(\frac{PnL_{own,i} + 0.1 \times Max[PnL_{flw,i}, 0]}{PnL_{own,i}}\right),
\end{aligned}
\tag{3}
$$

where the average ($Avg_{i\in\{I,t\}}$) is taken over all positions ($i$) of a portfolio ($I$) that were closed on the $t$-th day from the time the portfolio reached the first page of the leaderboard (i.e., had a top-18 or top-20 30-day ROI ranking) ($T_{Top}$). $PnL_{own,i}$, $PnL_{flw,i}$, and $PnL_{tot,i}$ denote the direct profits from the position itself, the profits copiers/followers made from betting on that position, and the total profits (i.e., the sum of direct and indirect profits) for that position, respectively.

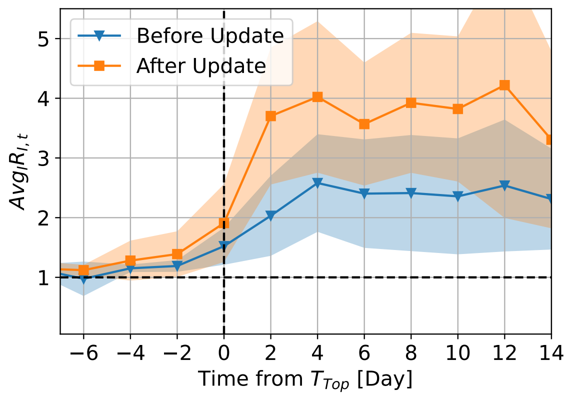



**Figure 11: Average profit ratio ($Avg_I R_{I,t}$) starting one week before $T_{Top}$, the time at which a portfolio appears on the first page of the leaderboard, and up to two weeks after $T_{Top}$. Light blue and light orange areas show the 95% confidence intervals.**

Figure 11 shows the evolution of this ratio $Avg_I R_{I,t}$ over time, starting one week before the portfolio made it to the (main) leaderboard page, all the way until two weeks after its inclusion in the leaderboard page. The blue curve shows what happened before TraderWagon changed its interface in March 2023; the orange curve shows what happened after the update. Clearly, the immediate jump after $T = 0$ for both curves indicates that appearing in the leaderboard has an immediate impact on indirect profits. In fact, *leaders holding a portfolio listed on the leaderboard page make over half to three quarters of their total profit from copiers' commissions.* This further substantiates our claim that leaders have very strong economic incentives to attempt to game leaderboard rankings.

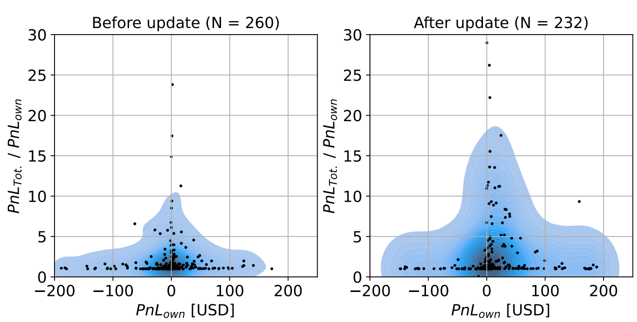
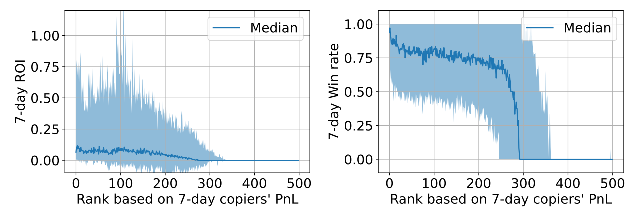



**Figure 12: Portfolios' average ratio of total profit over direct profit, for fourteen days from the time they are listed on the first page of the 30-day ROI ranking ($Avg_{t\in(0,\ldots,14)} R_{I,t}$), as a function of the portfolios' own profit in the same time period ($Avg_{t\in(0,\ldots,14)} [Avg_{i\in\{I,t\}} PnL_{own,i}]$). The blue shaded area represents the distributions' kernel density estimation (KDEs). Portfolios with more than USD 200 in absolute value are omitted in the KDE analysis. The number ($N$) in each figure's title shows the number of portfolios plotted in the figure.**

Next, we plot, in Figure 12, the average ratio of total profit over direct profit for fourteen days from the time the corresponding portfolio is listed on the first page of the 30-day ROI ranking ($Avg_{t\in(0,\ldots,14)} R_{I,t}$) against the portfolio's direct profit in the same time period ($Avg_{t\in(0,\ldots,14)} [Avg_{i\in\{I,t\}} PnL_{own,i}]$).

The figure shows that in both cases (before, and after the update), high profit source ratios come from very low direct profits. In other words, there appears to be a strong incentive for leaders to maximize ROI at the expense of the PnL. For instance, somebody that turns a USD 1 investment into USD 2 would have a 100% ROI, but only a USD 1 PnL. While a USD 1 PnL is not impressive, a 100% ROI would probably guarantee a spot in the leaderboard, and with that, a large number of copiers since only top portfolios in ROI are visible to copiers. In other words, ROI-based ranking seems to incentivize leaders to take potentially risky bets, but without much at stake, thereby creating a dangerous moral hazard.




**(a) ROI** **(b) Win rate**

**Figure 13: The relationship between the ROI (left) and win-rate (right) for the portfolios and the ranking based on the 7-day followers' PnL. The win rates (close to) zero for below 300th portfolios come from their dormancy.**

## 5.4 Bybit: Impact on copier profits

In Bybit, the leaderboard orders portfolios by 7-day PnL aggregated over all followers. We next delve into the impact of this ranking on overall profitability for copiers.

Figure 13 shows the relationships between a portfolio (direct) ROI (Fig. 13a) and their leaderboard ranking; and between win-rate and leaderboard ranking (Fig. 13b). We first notice that portfolios ranked around 300 and below appear to be mostly dormant—with zero ROI. For portfolios that have a positive PnL, we observe a slight decrease of both the (median) ROI and the (median) win-rate with the leaderboard ranking. This is not unexpected: 7-day aggregated PnL over all copiers is likely to be at least modestly correlated with the ROI; what is more surprising to us is that the correlation, if any, is quite weak. We next look at the influence of the leaderboard ranking on copiers' PnL. Figure 14 shows that the aggregated PnL over all copiers of a given portfolio exponentially decreases with the leaderboard rank. This is expected as the leaderboard rank specifically relies on that metric. More interestingly, the figure also shows what happens when we normalize this aggregated PnL by the number of followers—the decrease is markedly smaller (and the numbers are small, in the order of USD 1–25 on average past the top 50 ranked portfolios), which means that the *number* of copiers a given portfolio has is the dominant factor for its ranking.

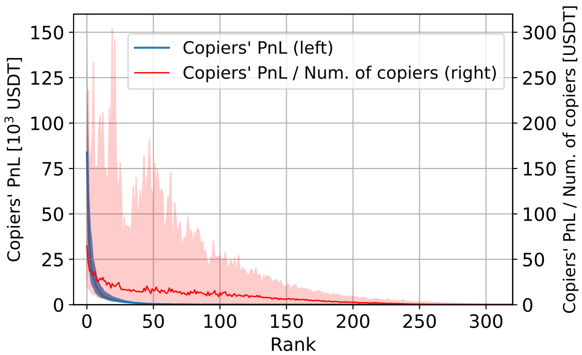
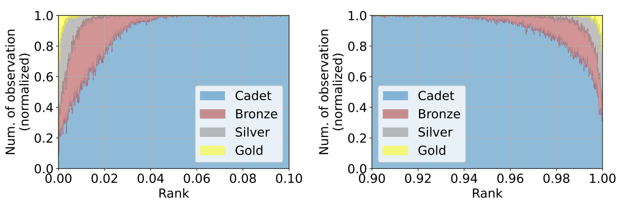



**Figure 14: Copiers' aggregated PnL and per-copier PnL as a function of the leaderboard rank on Bybit. Shaded areas show the 10th–90th percentile bands.**



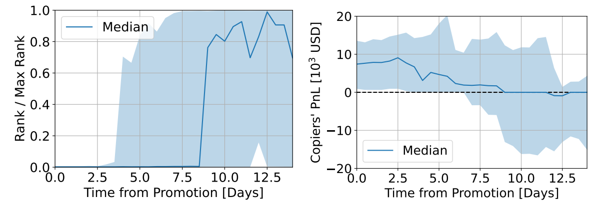

**(a) Top 10% rank** **(b) Bottom 10% rank**

**Figure 15: Ratio of observations at each rank in the 7-day followers' PnL ranking for each portfolio level: Cadet (lowest), Bronze, Silver, and Gold (highest). The left and right panel show the top and bottom 10% of the rankings in descending order, respectively.**

Combining the two results, copying top-ranked leaders does not lead to substantial investment profits.

We turn to the distribution of portfolio levels (Gold, Silver, Bronze, Cadet) over leaderboard rank in Figure 15. In that figure, rank is normalized between 0 (top rank) and 1 (lowest rank).[31] We show in the left panel the top 10% of portfolios, and in the right panel, the bottom 10%. As expected, there is a mix of higher-level portfolios among highly ranked portfolios. However, we also find a similar mix among the lowest ranked portfolios—while portfolios ranked in the middle are almost exclusively "Cadet." While initially surprising, this makes a lot of sense: higher-level portfolios can get more copiers—e.g., 2 000 for Gold compared to 100 for Cadet. Since leaderboard ranking in Bybit is based on the *aggregate* PnL over all followers, a losing position with a lot of copiers will perform disastrously according to that metric. Unfortunately, the figure indicates this does happen quite frequently: a number of copiers follow supposedly more reputable, higher-level portfolios, and end up, cumulatively, losing significant amounts of money. (Note that these losses may not be realized, since the positions may not be closed yet; nevertheless, it is fair to say that these positions are performing very poorly.) In short, being in a higher level means that the portfolio performance will have multiplicative effect over potentially large segments of the population.

[31] This normalization is necessary since the maximum number of portfolios increases over time.




**(a) The median rank of Gold-level portfolios** **(b) The median 7-day copiers' PnL of Gold-level portfolios**

**Figure 16: Gold-level portfolios' median leaderboard rank (left) and copiers' PnL (right) from the day they are promoted to the Gold level. Shaded areas denote the 25th–75th percentiles.**

We dig deeper on this aspect in Figure 16. First, we plot the evolution over time of the leaderboard rank of Gold portfolios (Fig 16a). We see that initially, Gold-level portfolios are also highly ranked in the leaderboard. Regrettably, this is short-lived: some portfolios start to dive in the rankings as early as two days after becoming Gold; and the majority collapses about six days later. This impacts the profits and losses of their (many) followers (Fig. 16b). For about one week, copiers make a profit, but their PnL plummets and even goes negative. In particular, the bottom 25% Gold portfolios lead to losses of more than USD 15 000 within ten days of their promotion to Gold. In other words, copiers have to be extremely attentive to the fate of the Gold portfolios they are copying, as losses can mount very abruptly. Unfortunately, having to pay such close attention to market movements is precisely what copy-trading platforms are—in theory at least—supposed to alleviate.

## 6 DISCUSSION

This section discusses the implications of our analyses.

### 6.1 Implications about design patterns

Our results show, through a quantitative analysis of real market data, that leaderboards, a prominent gamification feature [30], significantly affect copiers' portfolio choices. Specifically, our correlation coefficients (Figure 8 and 9) and regression results (Figure 10) evidence that leaderboard ranking order substantially affects the popularity of top-listed portfolios, confirming earlier results on click-through rates in the context of SERPs [29, 64].

These findings have two important implications. First, sorting, or ranking algorithms critically influence user behavior in high-stake situations. Our results support prior experimental studies that suggest a significant impact on our major decisions, such as Epstein et al. [25]'s experiment about SERP's influence on election polls, by providing an affirmative answer to the question of whether UI designs known to impact user behaviors in low-stake situations similarly affect them in higher (e.g., monetary) stakes. Second, UI design is crucial for online financial services. Our study demonstrates that UI designs substantially affect copier portfolio choices, even though a myriad of economics literature warns about related risks [19, 22, 35, 49]. Considering that many investors on the platforms we study are presumably individual investors, and that they invest non-negligible amounts of money (e.g., >USD 1 000), we observe a priori simple UI design decisions can foster substantial monetary risks. More broadly, this work calls for studying more closely the impact of user interfaces in online financial services.

## 6.2 Misaligned incentives for leaders

We have shown that on both platforms, copiers are overwhelmingly influenced by the leaderboard default rankings. We discuss how this situation fosters questionable incentives for leaders.

*TraderWagon portfolios and hedging.* We have shown that TraderWagon leaders can get significant profit in commissions from their copiers; crucially, this income is risk-free, since leaders only share in the *profits* of their copiers, and not in the losses. In other words, the commission scheme makes it attractive for leaders to quickly appear profitable, rather than patiently building a competitive investment history. Unfortunately, TraderWagon makes this a lot easier than it should be, by allowing each leader to create as many as six portfolios. A rational strategy is to take a range of opposite positions (essentially betting for and against everything on the market), with significant risk and potentially high leverage.

The idea is that the overall risk across all portfolios is close to zero, since the leader is completely hedging their positions, but that one of the portfolios is likely to get very high ROI and appear in the leaderboard, thereby capturing a bunch of copiers. If the portfolio can then hold its winning ways for a little bit longer, the leader can make significant profit from commissions, risk-free; if it does not, then the leader can simply close its portfolios, and try again. This situation creates a moral hazard, and should probably be prevented.

Even worse, a ranking purely based on ROI implies that a leader does not even need to invest a significant amount of money, since ROI is percentage-based, rather than an absolute measure of profit. To prevent abuse, copy-trading platforms should monitor the trading behavior of leaders, and probably only present data from leaders with a non-negligible amount of money at stake.

*Bybit and collusion.* Bybit's default ranking uses aggregated PnL across all followers. While different from TraderWagon's choice, this creates different but equally questionable incentives, especially since Bybit now offers the option for leaders to hold multiple "sub-portfolios," and offers no easy way for copiers to trace back these sub-portfolios to the same owner. Worse, a leader can also act as a copier, which means that leaders can simply copy their own portfolios to artificially inflate their aggregated follower PnL.

Here again, a winning strategy is to hedge bets across multiple portfolios, and copy each bet as much as possible to give the illusion of a strong aggregated follower PnL for whichever portfolio is winning. Different from TraderWagon, this strategy does require a more considerable amount of money to be invested by a leader, since PnL numbers are absolute, rather than relative profit. Nonetheless, a proper hedging strategy can make this investment almost risk-free, and let the leaders simply make profits from their copiers' commissions. Here, it is critical that copy-trading platforms ensure that users can clearly identify that different portfolios belong to the same individual, so that hedging strategies are obvious to potential copiers. Interestingly, Bybit set a policy that prohibits leaders from holding multiple portfolios for hedging purposes.[32] To which extent this policy is enforced in practice is unclear.

## 6.3 Misaligned incentives for platforms

Unfortunately, copy-trading platforms have incentives poorly aligned with mechanisms that could protect users. Trading platforms mainly profit from commissions on each trade, which incentivizes them to promote seemingly successful portfolios and downplay financial risks to copiers. These misaligned incentives appear to foster the use of manipulative designs, particularly gamification features. In a concerning trend, Binance and OKX, two of the top three crypto-exchanges (Bybit is the other one),[4] launched copy-trading services whose designs closely resemble TraderWagon and Bybit in late 2023. Furthermore, major copy-trading platforms for traditional financial assets also adopt similar design patterns.[33]

As we have shown, these interface designs, particularly leaderboards, can be gamed by unscrupulous leaders—who in fact have very strong incentives to do so. Worse, the current interface design is likely to indirectly cause financial hardship to novices. While copy-trading platforms arguably meet their self-professed goal of facilitating trading for novice investors, the cost seems high since those trades are likely disastrous.

## 6.4 Safeguard mechanisms

As a result, we argue that safeguard mechanisms to help copiers are crucial for copy-trading platforms to succeed on the long run. Currently, copy-trading platforms are designed to let copiers start trading right away. In Figure 1, TraderWagon advertises that users can "copy trade with one click," for instance. However, such frictionless design is at odds with copiers performing due diligence and more fully considering their options. Instead, as we have seen, users heavily rely on leaderboards.

Copy-trading platforms should recognize the negative impacts of the current interface designs both for users and, even more importantly, for themselves. Indeed, while frictionless designs, such as leaderboards and one-click trading, may contribute to short-term revenue increase for a copy-trading platform, the moral hazards these market mechanisms foster, by being easily gameable by aspiring leaders, may, down the road, cause users to lose all faith in the platform, leading to its eventual collapse. To avoid such a bleak future, platforms should work together to create sound design guidelines, including ethical website design practices. For example, displaying appropriate and timely warnings for high-risk investments, or building didactic content with the goal of improving user financial literacy would be highly valuable. In fact, Epstein et al [25] shows timely alerts substantially reduced biases induced by ranking algorithms. Studies evidence high financial literacy leads to better financial decisions [10, 31, 47]. Tutorial programs for new users may be particularly helpful [45]. Alternatively, it may be helpful to give users the autonomy to set up a user-driven UI to meet their investment goals [65]. Creating more specific design guidelines is a fruitful avenue for future research in the field.

[32] https://www.bybit.com/en/help-center/article/Master-Trader-Agreement-Copy-Trading

[33] https://www.zulutrade.com/leaders; https://www.etoro.com/discover/people/results

## 6.5 Which role for regulators?

While a fair and sustainable market structure is crucial for the long-run success of copy-trading platforms, it may be onerous for these platforms to voluntarily introduce safeguard mechanisms as it does not align with their (short-term) incentives to increase trading volume. As a result, many platforms may be reluctant to design and implement the modifications we argue are needed.

This is where regulators can play a role, by incentivizing or even mandating the adoption of safeguard mechanisms such as outlined above. Indeed, individual investors already bear significant investment risks [63]; the presence of manipulative design patterns magnifies these risks even more. As such, regulators are likely to step up efforts to protect consumers.

## 6.6 Limitations and future work

This work presents limitations common to empirical studies. First, our measurement period and the number of platforms studied may not be sufficient to fully capture all investor behaviors. Second, we could not perfectly disentangle all potential confounding factors. While TraderWagon and Bybit share similarities, they are not identical. Furthermore, we have to assume away potential transient effects (e.g., exchange rate fluctuations and shifts in investment trends) in this analysis.

A valuable direction for future studies would be to test the robustness of our findings with experiments more rigorously separating confounding factors. Another interesting extension to this study would be to studying other (copy-trading) platforms to confirm generalizability.

Last, our work only scratches the surface of how UI design influences investor decision-making process. Interviews or surveys would likely provide additional insights about how users decide which portfolios to copy.

# 7 CONCLUSION

This paper explores the trading behaviors of investors in TraderWagon and Bybit, two major copy trading platforms for cryptocurrency derivative products. In these platforms, novice traders ("copiers," or "followers") delegate their investment decisions to leaders, paying a share of their realized profit. Although the share of copy-trading in the entire cryptocurrency derivative market is still small, the customer base of copy-trading platforms base is steadily increasing. We saw that each leader, on average, is entrusted with more than USD 10 000 of follower funds.

These platforms extensively use gamification features, notably trading competitions, and "leaderboards," to promote supposedly high performing traders. We find, through correlation and quantile regression analyses, that copiers overwhelmingly follow leaderboard default rankings. Our finding is robust to 1) interface changes (as we have observed on TraderWagon during our measurement interval) and 2) specific choice of a ranking metric (Bybit and TraderWagon use drastically different metrics) – answering **RQ1** affirmatively.

Unfortunately, we also find that this strategy may not be particularly effective in terms of maximizing copier profit; often, positions collapse shortly after they appear on the leaderboard and start being extensively copied (in other words, we answered **RQ2** negatively).

More generally, we also showed that the current market designs create pernicious incentives (answering **RQ3** in the affirmative in the process): we outlined strategies for leaders to invest limited amounts of money, nearly risk-free, and create a constellation of portfolios that can lead them to acquire a decent follower base—and with it, a potential source of (risk-free) profit. The copy-trading platforms themselves unfortunately have little incentive to improve the situation, as they are mostly benefitting from trading volume rather than from providing tools for trading profitably.

While the picture this article paints is bleak, we believe it can foster considerably more work on how to better communicate to users the inherent risks of their activities. Many modern trading platforms, especially cryptocurrency trading platforms, embrace gamification features. However, as we have seen in this paper – and as has been extensively discussed in related work [63] – real money is at stake, and this makes these platforms closer to gambling outfits than to video games. We believe that effective messaging about the real risks of these investments is absolutely necessary to protect users; and, a redesign of the interfaces used by copy-trading platforms is also a must. Moreover, because of the aforementioned misaligned incentives, regulators might have to step in to ensure that this messaging is obvious to users. While copy trading may have not been in the spotlight until recently, the negative impact its design choices can have on users is already substantial; it is not too late to try to turn the tide.

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# A DETAILED DESCRIPTION OF TRADERWAGON

This section expands on TraderWagon's copy-trading system, complementing the discussion in Section 3.

## A.1 Relationship with Binance

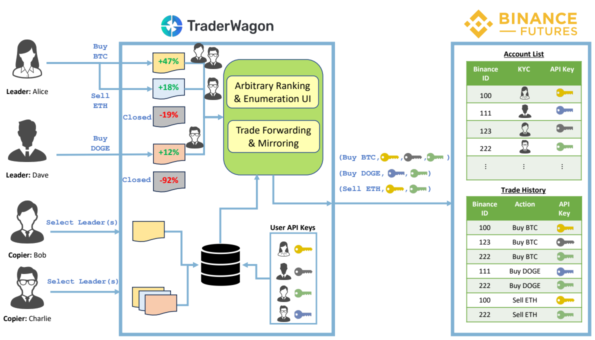


**Figure 17: System overview of TraderWagon. TraderWagon manages the API keys of all users, the portfolios owned by leaders, the web UI to aggregate and present the leader portfolios, the selections made by copiers, and the mechanics of mirroring leader trades to all of their copiers.**

TraderWagon uses its affiliation to Binance to provide its copy trading services. Figure 17 shows the relationship between the copy-trading service TraderWagon and the cryptocurrency exchange Binance. TraderWagon manages a set of portfolios that are maintained by leaders, along with the selections of portfolios that copiers wish to follow, as well as Binance API keys and a UI which allows copiers to enumerate and explore portfolios. When a leader makes a trade on a portfolio, TraderWagon automatically submits a corresponding transaction for all copiers to the Binance exchange.

## A.2 Leaderboard metrics

TraderWagon uses serveral metrics other than Profit and loss (PnL) and return on investment (ROI). The number of copiers ("copy traders") sort portfolios based on the number of copiers following them. The "win rate" metric ranks portfolios based on the percentage of positions that were closed with a positive PnL, regardless of the size of the position or of the PnL—so, for instance, a USD 0.01 position winning 0.1% would be counted as a win. The "maximum drawdown" (MDD) is the maximum percentage difference for a portfolio between its highest PnL and its lowest PnL.

## A.3 Fixed-amount option

With fixed-amount, the follower first selects the *total* amount of money they want to allocate to a specific leader portfolio, and then the (fixed) amount of money they want to invest in each portfolio position. Returning to our example, the follower would specify to invest, say, USD 500 to the leader portfolio, and USD 100 per position, leading them to acquire USD 100 of asset A, and USD 100 of asset B, *regardless of the specific percentages allocated by the leader* to assets A and B. In both fixed-amount and fixed-ratio, the copier also has discretion over when to start and stop copying—i.e., when they establish or close these positions, and some advanced parameters for copying.[34]

# B CORRELATION BETWEEN EXPLANATORY VARIABLES

Table 3 summarizes the correlation between explanatory variables and variance inflation factors (VIFs). It shows correlations are not strong enough to bias our regression analysis [18, 41, 55]. We also observe a low correlation between $I^{Top}$ and $I^{PnL}$—in other words, the indicator variables chosen can distinguish the effect of ROI- and PnL-based rankings.

# C PORTFOLIO POPULARITY

Our paper analyzes the influence of leaderboards on copiers' portfolio choice with *portfolio popularity*. We define it as the ratio between the number of copiers and the maximum number of copiers allowed for a portfolio. While portfolio popularity is helpful in including all data in correlation coefficient calculations and regression analysis, the maximum number of copiers allowed, being a variable, could bias our results. For instance, if a portfolio has an allocation of 100, 10 copiers would be 10% of the maximum quota. However, if the portfolio had an allocation of 200, 10 copiers would only be 5% of the maximum quota. We show here that this does not affect our conclusions.

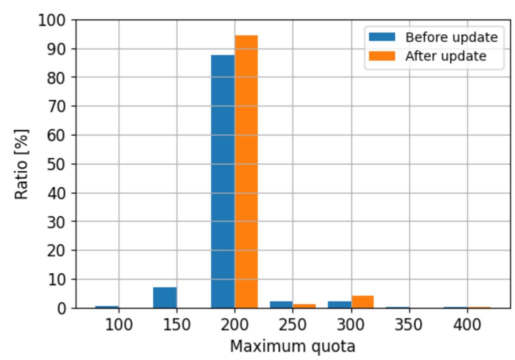


**Figure 18: The ratio of observation for each maximum number.**

*TraderWagon.* Figure 18 shows the ratio of observations for each maximum quota. The calculation only considers top-100 portfolios when ranked by 30-day ROI. Roughly 90% of observations involve portfolios with a maximum quota of 200; the rest is negligible. We obtain similar results when restricting ourselves to the top-20 portfolios instead.

Therefore, corrections due to differences in maximum quotas will be negligible in Pearson correlation coefficient calculation and regression analysis.

[34]https://traderwagon.zendesk.com/hc/en-us/articles/10752120216857-How-to-set-and-adjust-the-Stop-loss-Take-Profit-for-the-portfolio-

**Table 3: Correlations between explanatory variables**

| | Pearson Correlation | | | | | Cosine Similarity | | | | | VIF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\widehat{ROI}$ | $Age$ | $I^{Top}$ | $I^{PnL}$ | $I^{Rem}$ | $\widehat{ROI}$ | $Age$ | $I^{Top}$ | $I^{PnL}$ | $I^{Rem}$ | |
| $\widehat{ROI}$ | 1.000 | -0.091 | 0.597 | 0.123 | -0.067 | 1.000 | 0.164 | 0.618 | 0.175 | 0.020 | 1.575 |
| $Age$ | | 1.000 | -0.143 | 0.123 | 0.184 | | 1.000 | 0.356 | 0.306 | 0.415 | 1.067 |
| $I^{Top}$ | | | 1.000 | 0.076 | -0.197 | | | 1.000 | 0.187 | 0.000 | 1.628 |
| $I^{PnL}$ | | | | 1.000 | 0.012 | | | | 1.000 | 0.118 | 1.033 |
| $I^{Rem}$ | | | | | 1.000 | | | | | 1.000 | 1.073 |

*Bybit.* While leaders ranked in the Cadet class comprise the majority of observations (72.6%), those ranked in other classes – Bronze, Silver, and Gold – also have sizable weights in the observations within the top 300 in the 7-day aggregated copiers' PnL ranking (see Section 3 for the relationship between leaders' class and maximum quota). Therefore, we replicate the analysis in Section 5.1 for each class, by calculating the Pearson correlation coefficients for each class (i.e., maximum number) separately.

Table 4 summarizes the correlation between portfolio popularity and rank in selected metrics for each class. It clearly shows the same tendency as in Section 5 for all classes. Namely, the correlation between portfolio popularity and rank based on the 7-day aggregated copiers PnL ranking is higher than the 30-day ROI ranking. This result supports our conclusion that the default ranking on the leaderboard (i.e., the 7-day aggregated copiers' PnL ranking) has an outstanding influence on how copiers select portfolios to copy.

The modest correlation between life-long PnL and portfolio popularity is due to the fact that life-long PnL and 7-day aggregated follower PnL are correlated themselves. The positive correlation with the 30-day ROI ranking for leaders in the Gold class may be due to their quick decline in rank after they gained substantial copiers (See Section 5.4 for the details).

**Table 4: Pearson correlation coefficients between portfolio popularity and portfolio rank based on selected performance metrics.**

| | 30-day ROI | Life-long PnL | 30-day Win Rate | 7-day agg. copiers PnL |
|---|---|---|---|---|
| **Cadet** | **-0.193** | -0.471 | 0.206 | **-0.496** |
| **Bronze** | **-0.265** | -0.269 | -0.033 | **-0.476** |
| **Silver** | **-0.061** | -0.547 | -0.041 | **-0.468** |
| **Gold** | **0.242** | -0.516 | 0.177 | **-0.586** |