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Social Audience Size as a Reference Point: Evidence from a Field Experiment

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Abstract. In the dynamic landscape of the digital economy, social trading platforms are experiencing rapid growth. Our study delves into the impact of changes in social audience size—measured by the number of followers—on traders' performance and behaviors. Utilizing data from a company-led randomized field experiment conducted on a prominent cryptocurrency social trading platform, we unearth intriguing findings. Traders garnering increased social audience size exhibit tendencies to trade more frequently, utilize higher leverage, and, surprisingly, attain poorer performance. Notably, these adverse effects intensify among traders who previously excelled, suggesting a link to overconfidence. Interestingly, our research uncovers a reference point effect associated with social audience size. Removing accumulated social audience size does not alleviate the negative consequences, instead, they persist. Additionally, we observe an extra adverse effect when traders experience a reduction in the digit magnitude of follower counts, supporting our hypothesis about social audience size serving as a reference point. Our study carries significant implications for the design of social trading platforms. It serves as a crucial reminder for both traders and platform managers to carefully navigate the interplay between social audience size dynamics and trading decisions.

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1. Introduction

1.1. Motivation

With the rapid development of social media and financial technology (FinTech), social trading platforms such as eToro, ZuluTrade, and AvaSocial have garnered tremendous attention and attracted many users to record and share their trading experiences (Reith et al. 2020). According to a recent report (The Insight Partners 2022), the market size of social trading is expected to reach $3.8 billion by 2028, up from $2.2 billion in 2021. The number of registered users on eToro, the leading social trading platform, increased by 31% from the beginning of 2021 to the beginning of 2022, reaching 26.9 million total users worldwide.[1] As an increasing number of users engage in social trading platforms to see how their peers act (some platforms also allow for duplicate or copy trading), the influence of social trading in financial markets has become prominent (Apesteguia et al. 2020).

Social trading platforms enable users to obtain and share information, as well as learn about the trading decisions of their peers in large social networks. Individual traders benefit from the convenience of instant access to market information, the sharing of peer opinions, and the reviewing of their trading records offered by the platforms. Thus, many amateurs and professional traders alike are embracing social trading platforms. However, research into user activities and motivation on these online platforms is still in a nascent stage, and the dynamics of social audience size on trading behaviors have not been empirically examined.

In addition to the practice of social trading, prior studies on social influence and social interactions show that increased social audience size can motivate users to spend additional efforts and contribute more (Zhang and Zhu 2011, Huang et al. 2019). Most of these studies focus on user-generated content (UGC), where more efforts tend to translate to a higher level of performance in contribution quantity or quality. However, their conclusions may not apply to the context of social trading because trading involves uncertainty: More efforts in the context of trading (e.g., more frequent trading) do not necessarily lead to better outcomes (Thaler 2012). In this study, we aim to address this critical issue motivated by both social trading practice and literature on social interactions.

1.2. Research Questions and Contributions

Most prior literature on the use of social trading platforms (Oehler et al. 2016) focuses on followers who subscribe to receive notifications about a trader's trading activities rather than on traders themselves. Compared with conventional trading environments, social trading has a distinguishing feature, social audience, usually represented as the number of followers obtained by a trader on the platform (Rui and Whinston 2012, Dorfleitner et al. 2018, Venkatesan et al. 2021).[2] The impact of social audience size on traders' performance is substantially different and not straightforward. On the one hand, from a theoretical point of view, the impact could be positive because social images incentivize traders to exert more effort in achieving consistent and excellent performance and avoiding reputation loss (Glaser and Risius 2018).

However, on the other hand, social audience size might negatively affect trading performance by making traders more prone to be risk seeking, which can lead to irrational trading activity and worse performance (Park et al. 2013, Dorfleitner and Scheckenbach 2022). Thus, it motivates us to empirically investigate the impact of social audience size. Therefore, we ask our first research question: (1) *What is the effect of social audience size on traders' trading performance*? We bring clarity to this theoretically ambiguous question with an empirical investigation: a two-phase field experiment on a leading social trading platform that focuses on cryptocurrencies.[3] Compared with previous studies that mostly rely on observational data or laboratory experiments, our study draws conclusions from a field setting. Our randomized field experiment helps avoid endogeneity issues related to trading decisions and ensures that our conclusions are clean and less biased. In the first phase of the experiment, by manipulating the number of followers that traders receive, we find that increased social audience size hurts traders' performance in general. To further explore the reasons why social audience size negatively affects traders, we turn our attention to the changes in their trading behaviors, which are evidenced by trading records.

On social media, followers are known to have profound effects on user engagement and behaviors (Toubia and Stephen 2013, Qiu and Kumar 2017, Moqri et al. 2018, Venkatesan et al. 2021), so the same may be true on social trading platforms. The underlying mechanism behind the impact of social audience size on trading performance could be explained by the changes in trading behaviors. Therefore, we ask our second research question: (2) *How does social audience size affect trading behaviors*? The examination of this research question can help us better understand the underlying mechanisms of the negative effect of social audience size on trading performance (our first research question). The impact of social audience size on risk preferences in financial trading is unclear in the literature. On the one hand, traders may become more risk averse after their social audience size increases. Prior literature indicates that increased social audience size can create peer pressure such that traders may make a strategic plan to convey a positive self-image (Heimer 2016). In other words, the trader cares much about whether each trade is profitable, so they wait for relatively certain opportunities (i.e., they display risk aversion). On the other hand, increased social audience size may make traders more active and risk seeking (Apesteguia et al. 2020), because traders who receive more followers become more excited about the investments and willing to take more risks (Breitmayer et al. 2018, Pelster and Hofmann 2018). Both directions are theoretically plausible, which presents an opportunity for our empirical analysis.

Our empirical results show that traders whose social audience size increases open more positions and use higher leverage. In other words, increased social audience size leads to riskier, more aggressive trading. In addition, our additional analysis of the win rate demonstrates that such traders' decisions are of higher risk on average and more likely to be proven wrong afterward, which may indicate a higher level of overconfidence. These results explain why an increase in social audience size negatively affects trading performance (our first research question) by suggesting that increased social audience size causes overconfidence and leads traders to make risky trading decisions. The proposed mechanism of overconfidence is also supported by heterogeneity analysis: The effects of increased social audience size are stronger among traders who performed well prior to the increase in audience size, in which case they can reasonably conclude that they are gaining followers because of their skill as traders.

To gain further insights into the impact of social audience size, we ask our third research question: (3) *Are the effects of increased social audience size reversible with the removal of followers*? Although some prior studies have examined the impact of *increased* social audience size on individuals (Breitmayer et al. 2018, Lu et al. 2021), little is known about the *decrease* in social audience size, even though it is common in the context of social trading. Again, there is a theoretical basis for predicting reversibility or irreversibility, and the outcomes point to different mechanisms. On the one hand, the decrease in social audience size may curb the trader's risk-seeking inclination, causing them to rethink their trading decisions and carry out more discreet trading. If so, the decrease in social audience size should reverse the effects. Specifically, as mentioned earlier, increased social audience size leads traders to feel more confident about their decisions, trading more aggressively and using higher leverage. According to this logic, the decrease in audience size could lead traders to trade more cautiously, which suggests that the main force may be consistent with that revealed by the answers to the first and second research questions. If this is the case, then the effects of the decrease in audience size can be largely attributed to overconfidence (Dorfleitner and Scheckenbach 2022).

On the other hand, the loss of social audience size may induce more radical trading as the traders want to win back those lost followers. Prior research suggests that traders on social trading platforms usually fear losing followers, like other social media users, and traders may be driven by self-esteem to exert radical efforts to win back lost followers and restore their reputations (Chua and Chang 2016, Pelster and Hofmann 2018). If so, the negative effects of increased social audience size are not reversible. This finding would support the hypothesis that social audience size acts as a *reference point*, a concept from prospect theory (Kahneman and Tversky 1979).

According to prospect theory, an individual's utility has a kink around the reference point, where people place a heavier weight on perceived losses than on perceived gains relative to the reference point. Therefore, people are more incentivized to avoid perceived losses (being below the reference point). Prior studies have indicated that reference points significantly affect decision making in various contexts (Meng and Weng 2018, Kwark et al. 2021, He et al. 2022, Wang et al. 2022). In the context of social trading, social audience size accrues based on the trader's performance over time and represents the popularity of the trader in online trading communities. Traders who engage in such a community and share their real-time trading activities generally are highly attentive to their followers, so social audience size may become a reference point (Kahneman and Tversky 1979). When social audience size falls below the reference point (as occurs when we experimentally remove followers), traders may be irrationally desperate to return to the reference point (i.e., traders' recent perception of social audience size) by trading more aggressively (Baucells et al. 2011, Barasch and Berger 2014, den Boer and Keskin 2022).

Because follower counts fluctuate over time, the reference point is dynamic, which is consistent with the idea of the dynamic reference point in the literature. For example, dynamic reference points are observed in the context of stock trading, where investors' reference points shift based on market trends or personal investment history (Grinblatt and Han 2005). This can influence trading behavior, such as holding on to losing stocks too long or selling winning stocks too early. In negotiation literature, dynamic reference points play a role in shaping the aspirations and offers of negotiating parties. As negotiations progress, reference points can shift based on the information disclosed, the progress of the negotiation, and the actions of the other party (White and Neale 1994). The literature on consumer behavior discusses how consumers dynamically adjust their reference points based on past experiences, market conditions, or comparisons with others (Hardie et al. 1993).

In the second phase of the field experiment, we remove followers from some traders who gained followers in the first phase. Our results reveal that reducing social audience size surprisingly leads to even worse performance. In other words, the effects of social audience size are not reversible. We find that traders who experience audience size reduction exhibit more aggressive trading patterns, which implies that they may treat the original level of social audience size as a reference point and try to win followers back by trading more aggressively. To be specific, removing some of the followers makes the audience size fall below the established reference point. In our context, to gain more followers to go back to the reference point, the traders are more incentivized to trade more aggressively and try to achieve better performance. To further confirm the underlying mechanism, we also examine the heterogeneous effects of social audience size reduction. Drawing on prior research related to reference point theory, it is suggested that traders may assign importance to the digit magnitude of specific values, exhibiting a round-number bias (Chen 2018, Hervé and Schwienbacher 2018). Specifically, if social audience size acts as a reference point, then we should observe an additional negative effect among traders experiencing a decrease in the digit magnitude of follower counts (e.g., from three digits to two). Our empirical results support our hypothesis and provide further evidence of social audience size as a reference point.

To the best of our knowledge, our study is the first empirical examination of the impact of social audience size on trading performance on social trading platforms.

More importantly, our study is the first to focus on both increased and decreased social audience size, and we find that its impact is irreversible. From a theoretical perspective, our findings contribute to the broad literature on FinTech and social media and add to the understanding of how social audience size reshapes user engagement and performance. Our results show that social audience size has a significant impact on traders' performance and trading behaviors, the increased audience size may induce overconfidence, and the decrease in audience size may involve a reference point effect. Despite the abundance of findings in the literature, we discover that overconfidence manifests in reaction to anonymous followers. From a managerial perspective, our study offers important implications for the design of social trading platforms and reminds traders and platform managers to pay close attention to the interaction effect between social audience size and trading decisions.

2. Literature Review

2.1. Social Influence and Social Interactions

Many prior studies have examined how social interactions (e.g., social audience's following) affect an individual's behavior online. Zhang and Zhu (2011) provide empirical evidence that the group size of online communities has a positive causal effect on users' contribution to online public goods, such as UGC on Wikipedia. Similarly, Goes et al. (2014) suggest that as users' popularity increases with social interactions (e.g., more followers), users are motivated to make extra efforts and contribute more UGC. Popularity can also be conveyed in the form of awards from other users to make users feel they are recognized by the community, thereby making more efforts and contributions (Gallus 2017, Kumar and Qiu 2021, Burtch et al. 2022). The effect of social interactions on users' efforts to contribute is not one way. Rather, the increased quantity or quality of contributions, in turn, will help users obtain even higher popularity and more opportunities to interact with other users (Shriver et al. 2013). In addition, firms are also motivated because social interactions online (e.g., the "likes" button) help them attract users and encourage UGC about their brand, thereby promoting users' purchase intention (Phua and Ahn 2016, Mochon et al. 2017, Yang et al. 2019).

A growing stream of literature also explores the mechanisms underlying the effect of social interactions on users' online efforts. Toubia and Stephen (2013) indicate that increased social interactions can shift users' intrinsic utility to self-image utility, and therefore, users are motivated to spend higher efforts on high-quality content that can improve their self-image. Barasch and Berger (2014) demonstrate that when facing a large audience, users tend to focus on themselves, and they are more willing to share content that can maintain their self-image. Sun et al. (2017) highlight that the effect of group size on UGC is especially salient when user contributions are driven purely by nonmonetary rewards.

Despite the extensive findings, most prior studies are in the UGC context, and their main results can be summarized as that increased social interactions motivate users to spend additional efforts on and contribute more to UGC in quantity or quality. The uncertainty level is low in the UGC context because more efforts tend to translate into a higher level of performance (e.g., UGC quantity or quality). However, in our contexts of interest, social trading involves high uncertainty, and more efforts do not necessarily lead to better outcomes. For example, more efforts in the context of social trading may lead to more frequent trading (e.g., opening more positions) or riskier, more aggressive trading. In behavioral economics and finance literature, more frequent trading may lead to a lower level of trading performance in financial markets (Chen et al. 2007, Thaler 2012, Liu et al. 2014).

In addition, most prior research focuses on the impact of increased social interactions, usually in the form of an increased number of likes, the number of followers, or additional notifications (Toubia and Stephen 2013, Goes et al. 2014, Gallus 2017, Burtch et al. 2022). One exception is Zhang and Zhu (2011), wherein the authors leverage the block of Chinese Wikipedia as an opportunity to investigate the effects of decreased social audience size. However, our study focuses on both increased audience size and decreased audience size. In particular, whether the effects of increased social audience size are reversible remains unclear in the literature, and we test the reversibility by removing the increased followers in a two-phase field experiment design.

2.2. Reference Points and Trading Behavior

Prospect theory suggests that people evaluate outcomes as gains and losses relative to reference points, which vary between people and situations (Kahneman and Tversky 1979). Prospect theory explains a multitude of empirical puzzles concerning the irrational loss aversion of decision makers and the associated distortion of their behaviors (Tversky and Kahneman 1991, Tan and Zhang 2021). For example, individuals overestimate the value of their endowments (Kahneman et al. 1990), game players stop playing once they achieve their best score (Anderson and Green 2018), and consumers form higher expectations for sellers with high online ratings (Wang et al. 2022).

Reference points are also of great interest in financial settings, where they can explain certain trading behaviors. In the disposition effect, traders are prone to close a winning position but hesitate to close a losing position (Odean 1998). In the house money effect, people become more risk seeking if they earn a prior gain; in the break-even effect, a chance to break even is more attractive in the presence of a prior loss (Thaler and Johnson 1990). A trader's initial wealth and expected final wealth can also become reference points (Barberis and Xiong 2009, Meng and Weng 2018). All these studies focus on reference points derived from monetary factors, whereas we focus on social audience size as a reference point that is nonmonetary but may still affect trading behaviors on a social trading platform.

The development of information systems has led to an enormous rise in the popularity of FinTech (Fu et al. 2021, Hendershott et al. 2021), which provides digitalized and personalized trading services and can profoundly change traders' decision-making processes (Duz Tan and Tas 2021). Social trading platforms are a unique online social network context where traders can interact with each other directly (Reith et al. 2020), raising the possibility that social factors could become new reference points that influence trading behaviors. Our novel investigation of social audience size as a reference point that may affect behavior and performance on social trading platforms contributes to a more complete picture of the irrationality and decision-making processes of traders in the digital era.

2.3. Social Trading and Social Audience

Social trading platforms such as eToro, ZuluTrade, and AvaSocial are increasingly popular for their flexibility, efficiency, and accessibility to the wisdom of the crowd (Reith et al. 2020). On social trading platforms, interactions between traders and their followers make it possible to profit from the knowledge of others while communicating investment ideas (Dorfleitner et al. 2018). Platforms vary in the incentives offered for trading activities. On platforms that treat social trading as a service, selected traders can earn monetary incentives such as subscription fees in exchange for sharing trades that can be copied by subscribers (Apesteguia et al. 2020, Deng et al. 2024). On platforms that treat social trading as a channel of communication, traders may share trading ideas out of the desire to communicate with others, obtain social audiences, or improve their reputation (Breitmayer et al. 2018).

Social audience, a feature that distinguishes social trading from traditional trading environments, is usually represented as a trader's number of followers (Glaser and Risius 2018). Previous studies have corroborated that follower count is a crucial metric for gauging received social audience size (Rui and Whinston 2012, Barasch and Berger 2014). In online social networks, social audience motivates users to contribute content and stay active (Toubia and Stephen 2013, Sciara et al. 2023). Users who receive more social audiences tend to become more confident in their opinions, and social networks may even promote overconfidence and thus become a catalyst for narcissism (Davenport et al. 2014, Barry and McDougall 2018, Hawk et al. 2019). Nevertheless, social audiences can become a burden to users. The need to raise audience size and approval from peers may induce anxiety, such that users may exhibit negative emotional responses if they do not receive as much audience as expected (Spielberger and Reheiser 2009, Li et al. 2018). Low self-esteem and insecurity may drive extra self-presentation efforts to obtain peer recognition (Chua and Chang 2016).

Prior research also indicates that social audience size can affect risk preferences in trading behaviors. Some studies find that the audience size makes traders more confident and risk *seeking*. Traders who receive more social audience become more excited about investments and willing to take more risks (Pelster and Breitmayer 2019), perhaps to the point of overconfidence, have more active trading activities, and even accept negative returns (Liu et al. 2014, Breitmayer et al. 2018, Glaser and Risius 2018, Dorfleitner and Scheckenbach 2022). In particular, traders' overconfidence has been extensively studied, building on the work of Thaler and Johnson (1990) and subsequent research. For example, Statman et al. (2006) validate the common belief that traders become more overconfident following positive portfolio returns. Cheng (2007) observes increased overconfidence among traders with greater peer interactions. Grinblatt and Keloharju (2009) report that overconfident traders tend to engage in more frequent trading. In addition, the disposition effect is weaker on social trading platforms than on other types of platforms (Lukas et al. 2017, Gemayel and Preda 2018). Other studies suggest that social audience size makes traders more risk averse. The social trading environment comes with peer pressure, such that traders make strategic plans to convey a positive self-image (Heimer 2016). In addition, the disposition effect can be deepened by social audience size because of the increased fear of reputation loss (Pelster and Hofmann 2018).

The net effect of social audience size on risk preferences in the social trading environment remains empirically unclear. We investigate the effect in a context that involves no direct communication, which allows for a cleaner identification of the effect than in existing studies that focus on information transmission or social communication (Sui and Wang 2022, Deng et al. 2024). Moreover, we introduce the reference point as a useful theoretical perspective that has not previously been used to understand how social audience size affects trading behaviors.

3. Randomized Field Experiment

3.1. Research Context

We report a randomized field experiment (A/B test) conducted on one of the world's largest social trading platforms, which focuses on cryptocurrency trading. As of July 2023, the platform has more than 150,000 active traders who share their trading activities and more than 1.4 million registered users.[4] We choose to collaborate with this platform for three reasons. First, the platform treats social trading as a communication channel rather than a service, so traders do not receive monetary incentives for sharing their activities. Thus, trading behaviors and performance are affected by social audience size and other social factors alone, and we do not need to worry about monetary incentives as a confounding factor. In addition, the platform strives to encourage users to follow traders, thereby augmenting overall user engagement. This emphasis on the "follow" feature is pivotal in facilitating our analysis of the impact of social audience size within the platform's ecosystem.

Second, traders are required to link their accounts to the application programming interface (API) of a cryptocurrency exchange (e.g., Binance, BitMEX, or Bybit) before sharing any trading activity. Hence, all disclosed trading activities are reliable and displayed in real time. The platform also provides detailed information about each trader's behavior and performance. As shown in Figure 1, each trader's account page (visible to all traders on the platform) displays assets, profits, current positions, and the cumulative return rate. In addition, we can obtain historical position details like the open position price, close position price, leverage ratio, and profits. In short, we can gain insight into each trader's behaviors, which reflect their risk preferences and confidence, so that we can better understand the ultimate effects of social audience size on trading performance.

Third, the platform's focus on cryptocurrencies is valuable to us because cryptocurrency trading is not well understood in the literature despite the recent, dramatic development of cryptocurrency markets. In addition, most cryptocurrency markets are open 24/7, so the effects of social audience size on a trader's behavior can manifest more immediately in cryptocurrency markets than in traditional markets, which makes the platform a more practical and efficient environment for our research.

We measure social audience size using the number of followers, as illustrated in Figure 2. Each trader can see their number of followers but no information about the individual followers; other users also can see a trader's number of followers. Hence, the number of followers is the only salient metric with which a trader can gauge their own social audience and with which other users can evaluate the popularity of a trader. Although most trading information is public on the platform, following a trader is the only way to receive real-time notifications about trading activities, which are critical given that trading is time sensitive.

3.2. Experimental Design and Procedure

A user's decision to follow a trader is an individual decision based on factors that are unobservable to us, so the task of estimating the causal effects of social audience size on trading outcomes comes with endogeneity concerns. To address this issue, we reported a

Figure 1. (Color online) Screenshots of Trading Information on the Platform

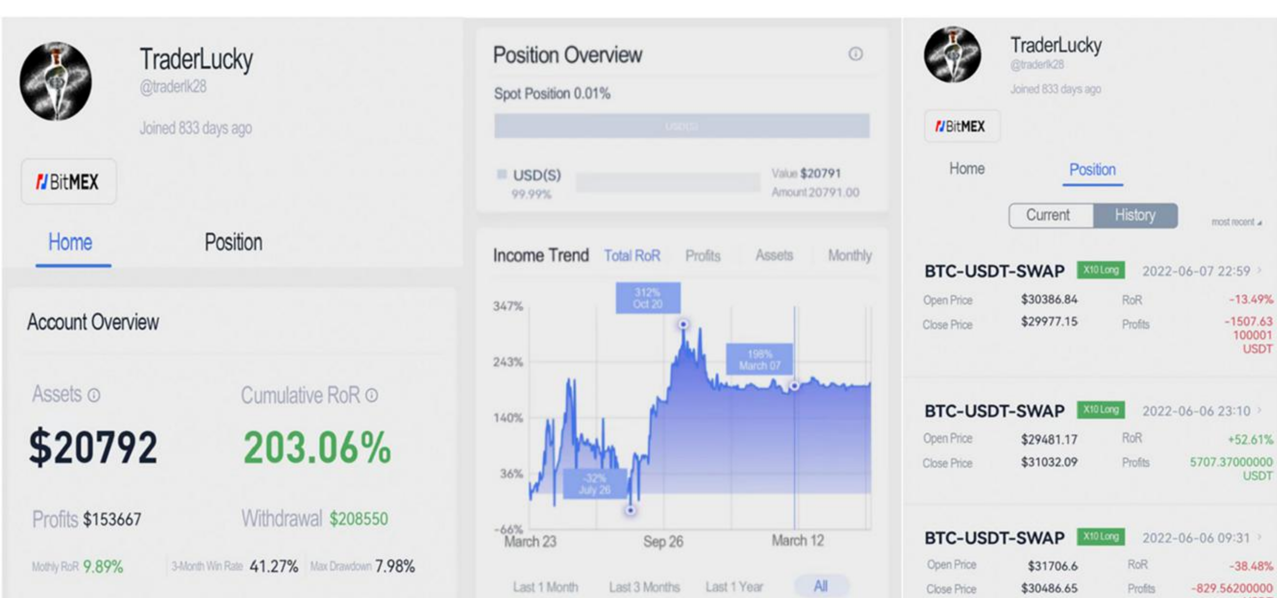
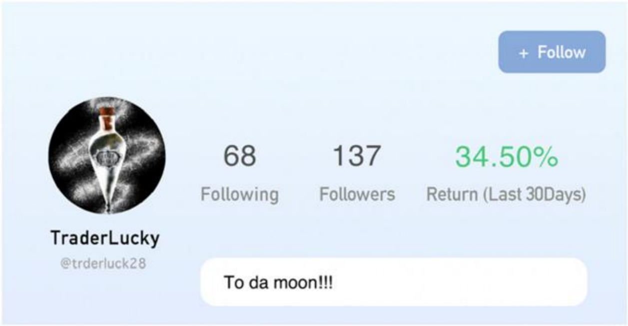


Figure 2. (Color online) Screenshot of the Account Page



randomized field experiment conducted by the management company of the platform with the exogenous manipulation of audience size. A total of 12,000 active traders were randomly selected on the platform; a trader is "active" if he or she opened or closed at least one position during the four-week pretreatment observation window and if the connected API was valid. Note that this user size was selected out of a caution principle of the platform. Because the platform was uncertain about the potential impact of adding followers on existing users, they refrained from introducing this function across the entire platform but opted for a randomized selection of a user sample to conduct this experiment.

In the experiment, traders were divided into two distinct categories based on their follower count at the onset of the pretreatment phase. This division was based on the understanding that different initial levels of social audience size would necessitate varying changes in follower numbers to ensure the effectiveness of the intervention. To this end, we rely on a key criterion: whether their follower count exceeded nine, which represented the median value among all traders. Each of these categories was then further divided into four groups, totaling eight distinct groups, each containing an average of 1,500 traders.[5] This arrangement is comprehensively detailed in Table 1.

To investigate the impact of varying degrees of social audience size, participants were assigned to different groups and subjected to specific interventions over a period of eight weeks, segmented into two four-week phases. Figure 3 visually illustrates the timeline of the treatment phases. Our observation window spans from July 8 to September 29, 2023, consisting of a pre-experiment observation phase (July 8–August 4, 2023) and the experimental phase (August 5–September 29, 2023). Throughout this period, Bitcoin prices fluctuated between $25,796 and $29,101, encompassing both upward and downward movements, which allows us to ensure that the observed results are not driven by a single market trend. Notably, within the entire pool of traders, the 25th percentile for follower count is 3, and the 75th percentile stands at 36.25. Aiming to approximately double the follower count for a median-level trader in two distinct categories, the following intervention sizes were selected: for the "Low" (L) category, interventions involved either adding or removing one follower weekly or maintaining the follower count unchanged; conversely, in the "High" (H) category, the interventions consisted of either adding or removing nine followers weekly or no intervention. This design was intended to ensure a substantial variation in audience size for the traders, thereby potentially inducing significant alterations in their trading performance and behavior.

Specifically, in the first four weeks, Groups 1–3 and 5–7 received a consistent increase in followers as per their respective intervention plans. This phase aimed to assess the immediate impact of heightened social audience size. In the subsequent four weeks, these groups underwent varied treatments: Groups 1 and 5 had followers removed, Groups 2 and 6 continued to gain followers, and Groups 3 and 7's follower count remained unchanged, effectively serving as a control group in the second phase. Additionally, Groups 4 and 8 experienced no changes in follower count throughout both phases and functioned as control groups. This approach was designed to test the persistence and potential reversibility of any effects observed in the first phase. By comparing the outcomes within and across these groups, we aimed to gauge the nuanced effects of fluctuating audience size on traders' behavior and performance.

4. Data

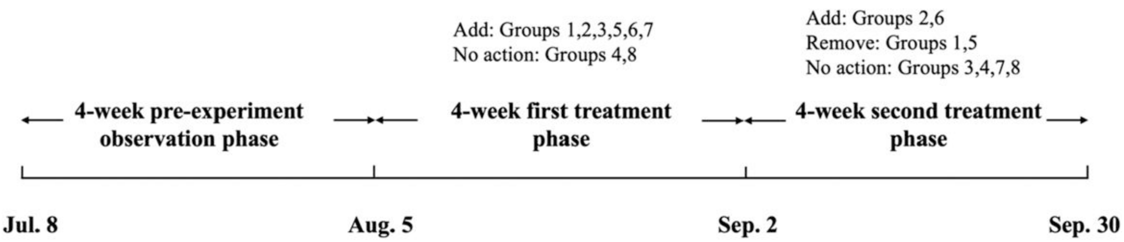
4.1. Data and Variables

Our raw data can be divided into three categories. First, we retrieved the treatment assignments from the

Table 1. Group Assignment and Treatment Plan

Group no.	Range of *FollowerPre*	Treatment in the first four weeks	Treatment in the last four weeks
1: Treatment A_low	≤9	Add 1 artificial follower/week	Remove 1 artificial follower/week
2: Treatment B_low	≤9	Add 1 artificial follower/week	Add 1 artificial follower/week
3: Treatment C_low	≤9	Add 1 artificial follower/week	No intervention
4: Control_low	≤9	No intervention	No intervention
5: Treatment A_high	>9	Add 9 artificial followers/week	Remove 9 artificial followers/week
6: Treatment B_high	>9	Add 9 artificial followers/week	Add 9 artificial followers/week
7: Treatment C_high	>9	Add 9 artificial followers/week	No intervention
8: Control_high	>9	No intervention	No intervention

Figure 3. Timeline of Treatment Phases



randomization system. Second, the number of followers for every trader is monitored every week during the observation window (July 8–September 29, 2023). Third, we stored each user's transaction data during the observation window. To protect privacy, we de-identified our data before variable construction and analyses.

To be consistent with the level of treatment, we aggregated the data to conduct main analyses at the trader level. Tables 2 and 3 provide the descriptions and descriptive statistics of the numerical variables. Our outcomes of interest are (i) the return rate, which captures the trader's financial performance, and (ii) the number of positions opened, win rate, and leverage, which characterize the trader's behavior patterns.

More specifically, the return rate in our paper is measured as the gain or loss divided by the initial total assets. For open positions, their unrealized profit and loss are included in the return rate calculation. This provides a standardized measure of trading

Table 2. Variable Descriptions for the Trader-Level Cross-Sectional Data

Variable	Description
Treatment related	
Treat1st	A binary treatment indicator for the first phase: 0 = no manipulation of followers (Groups 4 and 8), 1 = add followers every week (Groups 1–3 or 5–7)
TreatDec2nd	A binary treatment indicator for the second phase: 1 = decrease followers every week (Group 1 and 5), 0 = do not decrease followers every week (Other Groups)
TreatInc2nd	A binary treatment indicator for the second phase: 1 = add followers every week (Group 2 and 6), 0 = do not add followers every week (Other Groups)
FollowerPre	The number of followers at the beginning of the pretreatment phase
Follower1st	The number of followers right before the treatment of the first phase
Follower2nd	The number of followers right before the treatment of the second phase
FollowerHigh	A binary variable indicating whether the variable *FollowerPre* > 9
Trading related	
Tenure	The number of days since the trader signed up for this platform
TotalAssetsPre	The trader's total assets in million dollars at the beginning of the pretreatment phase
TotalAssets1st	The trader's total assets in million dollars at the beginning of the first experimental phase
TotalAssets2nd	The trader's total assets in million dollars at the beginning of the second phase
ReturnRatePre	The financial returns during the pretreatment phase divided by the total assets at the beginning of the pretreatment phase
ReturnRate1st	The financial returns during the first phase divided by the total assets at the beginning of the first phase
ReturnRate2nd	The financial returns during the second phase divided by the total assets at the beginning of the second phase
WinRatePre	The ratio of the number of positions with positive returns to the total number of positions in the pretreatment phase
WinRate1st	The ratio of the number of positions with positive returns to the total number of positions in the first phase
WinRate2nd	The ratio of the number of positions with positive returns to the total number of positions in the second phase
NumPositionsPre	The number of opening position operations in the pretreatment phase
NumPositions1st	The number of opening position operations in the first phase
NumPositions2nd	The number of opening position operations in the second phase
AverageLeveragePre	The average proportion of borrowed funds used in their investment activities relative to their own capital in the pretreatment phase
AverageLeverage1st	The average proportion of borrowed funds used in their investment activities relative to their own capital in the first phase
AverageLeverage2nd	The average proportion of borrowed funds used in their investment activities relative to their own capital in the second phase

Notes. To be more concise, we omit the notation to indicate that these variables are at the trader level. We only include u in the model specification, such as $Treat1st_u$. The same applies to all the following tables.

Table 3. Descriptive Statistics for the Trader-Level Cross-Sectional Data

Variable	Mean	Standard deviation	Median	Minimum	Maximum
Treatment related					
Treat1st	0.76	0.43	1	0	1
TreatDec2nd	0.26	0.44	0	0	1
TreatInc2nd	0.25	0.43	0	0	1
FollowerPre	61.43	292.35	9	0	7,317
Follower1st	67.89	314.31	11	0	7,982
Follower2nd	89.10	340.93	20	0	8,586
FollowerHigh	0.54	0.50	1	0	1
Trading related[a]					
Tenure	378.56	355.93	256	1	2,399
TotalAssetsPre	0.02	0.10	0.00	0.00	4.68
TotalAssets1st	0.02	0.18	0.00	0.00	15.33
TotalAssets2nd	0.02	0.24	0.00	0.00	14.32
ReturnRatePre	−0.09	1.24	−0.40	−1.00	32.90
ReturnRate1st	0.03	1.58	−0.43	−1.00	33.57
ReturnRate2nd	0.30	2.02	−0.22	−1.00	47.79
WinRatePre	0.45	0.12	0.45	0.00	1.00
WinRate1st	0.46	0.11	0.47	0.00	1.00
WinRate2nd	0.47	0.14	0.48	0.00	1.00
NumPositionsPre	27.27	12.52	26	1	94
NumPositions1st	32.93	14.83	32	0	96
NumPositions2nd	29.97	15.39	29	0	107
AverageLeveragePre	3.31	1.78	2.85	0.52	19.39
AverageLeverage1st	4.16	2.09	3.73	0.00	25.46
AverageLeverage2nd	3.75	2.15	3.30	0.00	29.92

[a]When there is not any trading activity in a given phase, all the trading-related variables are filled with zero. The results after removing inactive traders are provided in Online Appendix G.

performance. Furthermore, the number of positions opened refers to the number of distinct investments or trading positions that an investor or trader has entered into. A "position" in financial markets represents ownership or exposure to a particular financial instrument, such as stocks, bonds, options, or other derivatives. The number of positions opened is a key factor in assessing an investor's exposure to different assets and the overall risk profile of their portfolio. A substantial volume of opening position operations may suggest an aggressive trading strategy, often associated with elevated risk (Brogaard and Garriott 2019). We calculate the number of opening position operations in each phase.

Additionally, a trader's leverage (or leverage ratio) refers to the proportion of borrowed funds used in their investment activities relative to their own capital. It is a measure of the extent to which an individual is using borrowed money to increase the size of their investment position. The leverage ratio is calculated by dividing the total value of the investment position by the trader's own capital. According to the U.S. Securities and Exchange Commission (SEC), leverage amplifies both potential gains and losses, thus increasing the risk profile of a trading activity.

Finally, the win rate is the ratio of the number of positions with positive returns to the total number of positions based on the closed positions (realized value), because we can only determine whether a position has achieved positive returns after it is closed.

To facilitate a comprehensive examination of mechanisms and conduct thorough robustness assessments, we additionally assemble a trader-week level panel data set (eight-week experimental period). The variable descriptions and summary statistics are presented in Tables 4 and 5, respectively.

Prior to commencing any analytical procedures, we perform randomization checks across eight groups. The outcomes of these assessments, as outlined in Online Appendix A, demonstrate a high degree of balance across these groups.

4.2. Model-Free Evidence

Before conducting formal statistical analyses, we present model-free evidence to illustrate the differences in return rates resulting from the treatments. In Figure 4, we demonstrate that during the first phase of the experiment, an increase in social audience size leads to a decrease in traders' return rates, regardless of whether the traders' previous audience size was high or low. In Figure 5, we further show that not only does an increase in social audience size affect return rates, but a decrease in audience size can also trigger a reduction in return rates. Consequently, we examine the existence of statistical significance and explore additional mechanisms in the following sections.

Table 4. Variable Descriptions for the Weekly Panel Data

Variable	Description
Treatment related	
$TreatInc_{ut}$	A binary treatment indicator of whether there are follower increases caused by the treatment plan (1: Yes, 0: No) in the week t
$TreatDec_{ut}$	A binary treatment indicator of whether there are follower decreases caused by the treatment plan (1: Yes, 0: No) in the week t
$TreatFollowerChange_{ut}$	The number of followers changes caused by the treatment plan at the beginning of the week t
$Follower_{ut}$	The number of followers at the beginning of the week t after the treatment
$FollowerDigitDec_{ut}$	A binary variable indicating at the beginning of each week after the treatment, whether the digit magnitude of the number of followers falls (e.g., $Follower_{t-1} \geq 10$ and $Follower_t < 10$)
$NaturalFollowerChange_{ut}$	The natural number of followers changes during the week t
$TreatFollowerChangeRatio_{ut}$[a]	The ratio of $TreatFollowerChange_t$ to $Follower_{t-1}$
$NaturalFollowerChangeRatio_{ut}$	The ratio of $NaturalFollowerChange_t$ to $Follower_t$
$ObsFollowerChangeRatio_{ut}$	The ratio of ($Follower_t$-$Follower_{t-1}$) to $Follower_{t-1}$, which is also the sum of $TreatFollowerChange_t$ and $NaturalFollowerChange_{t-1}$
Trading related	
$ReturnRate_{ut}$	The financial returns during the week t divided by the total assets at the beginning of the week t
$ReturnRatePosLast_{ut}$	A binary indicator suggesting whether the trader makes profits in the last week of week t (i.e., $ReturnRate_{(t-1)} > 0$)
$WinRate_{ut}$	The ratio of the number of positions with positive returns to the total number of positions opened during the week t
$NumPositions_{ut}$	The number of opening position operations during the week t
$AverageLeverage_{ut}$	The average proportion of borrowed funds used in their investment activities relative to their own capital during the week t

Note. $Follower_{u,\,t-1} + NaturalFollowerChange_{u,\,t-1} + TreatFollowerChange_{ut} = Follower_{ut}$.
[a]If the denominator is originally zero, we replace it with one to conduct ratio calculation.

5. Data Analyses and Results

5.1. Research Question 1: Effect of Increased Social Audience Size on Trading Performance

We use the first-phase data to estimate the effect of increased social audience size on trader u's financial performance in terms of the return rate in dollars ($ReturnRate1st_u$).[6] The treatment variable is $Treat1st_u$, which indicates whether the treatment plan introduced additional follower (one for the L category or nine for the H category) for trader u every week in the first phase (so $Treat1st_u = 1$ for Groups 1, 2, 3, 5, 6, and 7 alike).

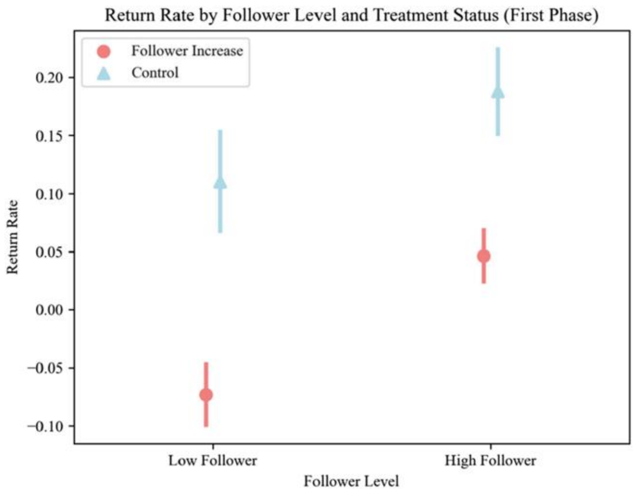
$$ReturnRate1st_u = \beta_0 + \beta_1 Treat1st_u + \epsilon_u \tag{1}$$

We report the regression results in Table 6. With *ReturnRate1st* as the outcome, the coefficients of *Treat1st* are significantly negative for the entire subject pool (full sample in column 3, $\beta_{Treat1st} = -0.161$, $p < 0.01$). This suggests that, under the current intervention, the

Table 5. Descriptive Statistics for the Weekly Panel Data

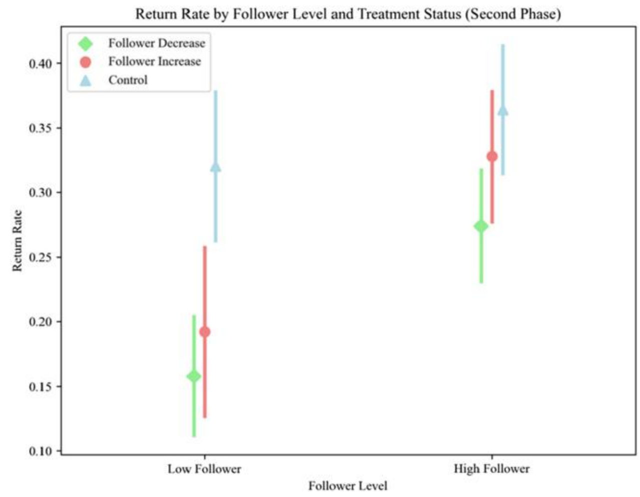
Variable	Mean	Standard deviation	Median	Minimum	Maximum
Treatment related					
$TreatInc_{ut}$	0.50	0.50	1	0	1
$TreatDec_{ut}$	0.13	0.33	0	0	1
$TreatFollowerChange_{ut}$	1.97	4.89	1	−9	9
$Follower_{ut}$	85.48	338.09	19	0	8,888
$FollowerDigitDec_{ut}$	0.01	0.10	0	0	1
$NaturalFollowerChange_{ut}$	1.39	8.19	0	−36	204
$TreatFollowerChangeRatio_{ut}$	0.08	0.19	0	−1	1.29
$NaturalFollowerChangeRatio_{ut}$	0.03	0.12	0	−0.29	3
$ObsFollowerChangeRatio_{ut}$	0.12	0.26	0.08	−1	4
Trading related					
$ReturnRate_{ut}$	0.04	0.60	0.00	−0.94	3.83
$ReturnRatePosLast_{ut}$	0.42	0.49	0	0	1
$WinRate_{ut}$	0.44	0.25	0.45	0.00	1.00
$NumPositions_{ut}$	7.86	5.22	7	0	36
$AverageLeverage_{ut}$	3.61	3.31	2.87	0	31.63

Figure 4. (Color online) Model-Free Evidence for the First Treatment Phase



Note. The mean represents the average return rate for each group, whereas the interval indicates one standard deviation, reflecting the variability around the mean.

Figure 5. (Color online) Model-Free Evidence for the Second Treatment Phase



Note. The mean represents the average return rate for each group, whereas the interval indicates one standard deviation, reflecting the variability around the mean.

average return rate during the initial phase experiences a decline from 15.3% (constant term) to −0.8%. The impact is relatively more salient among the traders with fewer prior number of followers (L category in column 1: $\beta_{Treat1st} = -0.183$) compared with those with larger prior social audience size (H category in column 2: $\beta_{Treat1st} = -0.141$).

To account for the wide range of return rates observed across the entire trader pool, we conduct supplementary analyses by excluding outliers, namely traders with return rates exceeding 90% or falling below −90%, as well as those who exhibit total inactivity during the first experimental phase. The estimation results, detailed in Online Appendix G (column 1 of Table G.1), indicate a significant negative treatment effect ($\beta_{Treat1st} = -0.082$, $p < 0.01$).

Besides, to gain a more comprehensive understanding of the treatment effect size, we employ the trader-week panel data set for estimating its impact. The results, presented in Online Appendix C (column 1 of Table C.1), reveal that the treatment leads to an average weekly return rate reduction of −3%. Additionally, we introduce a new treatment variable, $TreatFollowerChangeRatio_t$, to track the weekly change ratio in followers attributed to the treatment intervention. The findings, documented in Online Appendix D (column 1 of Table D.1), indicate that doubling the follower count (a 100% increase) in a week can cause an average 8.4% decline in performance ($\beta_{Treat1st} = -0.084$, $p < 0.01$). In light of this rationale, some may wonder whether the observed outcomes could be attributed to the substantial fluctuations in follower counts, potentially causing traders to feel weird. To address this concern, we conduct a series of pertinent robustness checks, the details of which are presented in Online Appendix E. We also report the results with control variables in Online Appendix N. All these additional analyses collectively provide valuable insights into the impact of social audience size on traders' performance.

The results resolve the theoretical ambiguity about the effect of increased social audience size in the social trading context: An increase in audience size leads to worse performance. One possible explanation is that increased audience size induces the traders to be risk

Table 6. Regression Results on Return Rate in the First Treatment Phase

	Dependent variable = *ReturnRate1st*		
	(1)	(2)	(3)
Treat1st	−0.183*** (0.050)	−0.141*** (0.043)	−0.161*** (0.032)
Constant	0.110*** (0.042)	0.188*** (0.036)	0.153*** (0.028)
Groups of subjects	1 to 4	5 to 8	1 to 8
Observations	5,516	6,484	12,000

Note. Robust standard errors are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 7. Regression Results on Average Leverage Level in the First Treatment Phase

	Dependent variable = *AverageLeverage1st*		
	(1)	(2)	(3)
Treat1st	0.467*** (0.073)	0.643*** (0.046)	0.569*** (0.043)
Constant	4.313*** (0.063)	3.243*** (0.038)	3.729*** (0.037)
Groups of subjects	1 to 4	5 to 8	1 to 8
Observations	5,516	6,484	12,000

Note. Robust standard errors are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

seeking and trade irrationally, suggesting an overconfidence effect. They may open positions even when the trading opportunity is not ideal, and they may also use higher leverage, resulting in lower performance in the end. To gain insight into the possible mechanism, we examine traders' behaviors in the next section.

5.2. Research Question 2: Effect of Increased Social Audience Size on Trading Behaviors

To further explain why the trading performances are different across groups, we use the first-phase data and analyze the impact of increased social audience size on subjects' trading behaviors to answer our second research question. Equation (2) is the same as Equation (1) except for the dependent variable, $Behavior1st_u$, which represents three first-phase variables: the average leverage level ($AverageLeverage1st_u$), the number of positions opened ($NumPositions1st_u$), and the win rate ($WinRate1st_u$).[7]

$$Behavior1st_u = \beta_0 + \beta_1 Treat1st_u + \epsilon_u \tag{2}$$

Examining the findings in Tables 7–9, we discern a notable impact of increased social audience size on traders' behavior. Specifically, as shown in Table 7, a rise in audience size is associated with a statistically significant increase in leverage utilization (full sample in column 3, $\beta_{Treat1st} = 0.569$, $p < 0.01$), indicating a predisposition toward riskier trading practices. This predisposition is further substantiated by the treatment's effect on the number of positions, as elucidated in Table 8. The results reveal that heightened social audience size prompts traders to initiate a significantly greater number of positions (full sample in column 3, $\beta_{Treat1st} = 4.517$, $p < 0.01$). The substantial volume of position openings may signify an aggressive trading strategy, a characteristic often linked to heightened risk (Brogaard and Garriott 2019). However, it is imperative to note that confidence in trading does not necessarily translate into improved decision making. As demonstrated in Table 9, an increase in social audience size is correlated with a significant decrease in the win rate (full sample in column 3, $\beta_{Treat1st} = -0.018$, $p < 0.01$), signifying that a larger proportion of positions result in negative returns.

The estimation results also reveal that the treatment's impact on H-category traders in terms of leverage and position volume is comparatively more pronounced than on those in the L-category traders (in columns 1 and 2 of Tables 7 and 8, $\beta_{Treat1st} = 0.643 > 0.467$, $\beta_{Treat1st} = 5.127 > 3.692$). Notwithstanding, posttreatment, H-category traders still exhibit lower risk profiles, after taking the baseline (constants) into account. Moreover, the win rates of H-category traders demonstrate a relatively smaller response to the treatment.

It is also imperative to consider the influence of market trends on trader behavior. Despite the general stability of the cryptocurrency market during the study period, concerns may arise regarding the potential impact of the price decline in the second week on the primary findings. However, as delineated in Online Appendix F, the treatment effects remain qualitatively consistent across both a stable week (week 1) and a declining week (week 2). Further corroborating this consistency, Online Appendix I presents findings from

Table 8. Regression Results on Number of Positions in the First Treatment Phase

	Dependent variable = *NumPositions1st*		
	(1)	(2)	(3)
Treat1st	3.692*** (0.500)	5.127*** (0.320)	4.517*** (0.296)
Constant	33.514*** (0.429)	26.169*** (0.261)	29.506*** (0.251)
Groups of subjects	1 to 4	5 to 8	1 to 8
Observations	5,516	6,484	12,000

Note. Robust standard errors are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 9. Regression Results on Win Rate in the First Treatment Phase

	Dependent variable = *WinRate1st*		
	(1)	(2)	(3)
Treat1st	−0.021*** (0.004)	−0.015*** (0.003)	−0.018*** (0.002)
Constant	0.463*** (0.003)	0.489*** (0.003)	0.477*** (0.002)
Groups of subjects	1 to 4	5 to 8	1 to 8
Observations	5,516	6,484	12,000

Note. Robust standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

a separate experiment conducted during an overall market downturn, yielding qualitatively similar results. Additionally, we conduct a subsample analysis of traders who achieved no pretreatment profits to test whether our results are driven by increased profits rather than an increase in the number of followers. As presented in Online Appendix M, the results continue to support our main findings.

Collectively, these findings suggest that heightened social audience size catalyzes traders into making increased and riskier investments, which are inclined to underperform. This aligns with the statement posited in Section 5.1, where social audience size is linked to an escalation in overconfidence, ultimately leading to financial detriment.

5.3. Research Question 3: Decrease in Social Audience Size and Reversibility of the Original Effect

We analyze data from the second-phase experiment to test the reversibility of the original effect, with implications for the mechanism by which the decrease in social audience size affects traders. On the one hand, the decrease in audience size might curb traders' risk-seeking inclination and lead traders to make more careful decisions, reversing the original effect of increased social audience size. On the other hand, the loss of audience size might cause traders to perceive that they have fallen below their reference point, leading to more irrational trading behavior.

For the L-category subjects, those in Groups 1, 2, and 3 received the same treatment in the first phase (an increase of one follower per week). Similarly, subjects in Groups 5, 6, and 7 also received the same treatment (an increase of nine followers per week). In the second phase, Groups 3 and 7 received no treatment, so we use them as the baseline to construct two dummy variables: $TreatDec2nd_u$, which captures whether the trader experienced a loss of the corresponding followers per week (one follower for Group 1, nine followers for Group 5), and $TreatInc2nd_u$, which captures whether the trader experienced additional followers per week (one follower for Group 2, nine followers for Group 6). We are primarily interested in the effect of decreased audience size here but we also include the increased audience size groups (Groups 2 and 6) to see how the overconfidence effects evolve (measured in Section 5.1).

The outcomes of interest, represented as $Outcome2nd_u$ in Equation (3), are financial performance ($ReturnRate2nd_u$[8]) and trading behavior ($NumPositions2nd_u$, $AverageLeverag2nd_u$, and $WinRate2nd_u$) in the second phase.

$$Outcome2nd_u = \beta_0 + \beta_1 TreatDec2nd_u + \beta_2 TreatInc2nd_u + \epsilon_u \tag{3}$$

The outcomes of our investigation are presented comprehensively in Tables 10–13. Initially, we focus on examining the estimated coefficients of *TreatDec2nd* to elucidate the potential reversibility of the impact of social audience size. As per Table 10, a decrease in audience size, relative to no change in audience size, introduces diminished return rates (in column 3, $\beta_{TreatDec2nd} = -0.122$, $p < 0.01$). Moreover, our findings

Table 10. Regression Results on Return Rate in the Second Treatment Phase

	Dependent variable = *ReturnRate2nd*		
	(1)	(2)	(3)
TreatInc2nd	−0.129 (0.087)	−0.036 (0.071)	−0.079 (0.055)
TreatDec2nd	−0.163** (0.074)	−0.090 (0.066)	−0.122** (0.049)
Constant	0.321*** (0.057)	0.364*** (0.049)	0.344*** (0.038)
Groups of subjects	1 to 3	5 to 7	1 to 3, 5 to 7
Observations	4,194	4,896	9,090

Note. Robust standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 11. Regression Results on Average Leverage Level in the Second Treatment Phase

	Dependent variable = *AverageLeverage2nd*		
	(1)	(2)	(3)
TreatInc2nd	0.103 (0.100)	0.184*** (0.056)	0.144** (0.056)
TreatDec2nd	0.203** (0.099)	0.461*** (0.059)	0.336*** (0.056)
Constant	3.918*** (0.070)	3.348*** (0.039)	3.615*** (0.039)
Groups of subjects	1 to 3	5 to 7	1 to 3, 5 to 7
Observations	4,194	4,896	9,090

Note. Robust standard errors are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

in Tables 11–13 reveal that a decrease in social audience size prompts traders to employ higher leverage (in column 3, $\beta_{TreatDec2nd} = 0.336$, $p < 0.01$), initiate a greater number of positions (in column 3, $\beta_{TreatDec2nd} = 2.047$, $p < 0.01$), and experience lower win rates (in column 3, $\beta_{TreatDec2nd} = -0.008$, $p < 0.05$). Notably, the adverse effect on return rates is more pronounced among traders falling within the L category (column 1 of Table 10, $\beta_{TreatDec2nd} = -0.163$, $p < 0.05$). We have also added a measure of trading frequency as additional evidence of irrational trading in Online Appendix P, showing consistent results. These results suggest that traders engage in more irrational trading behaviors. Specifically, the decrease in *WinRate* indicates that a higher proportion of their trades is incorrect or result in negative returns—In other words, their trading decisions are increasingly wrong.

The underlying reason is that, according to prospect theory, individuals tend to respond to perceived losses by increasing their efforts in an attempt to recover from those losses (Baucells et al. 2011). In our context, traders who experience a perceived loss—such as a decline in social audience size—are likely to intensify their trading efforts in the short term. Traders may feel compelled to take immediate action rather than adopting a more cautious, patient trading strategy, such as waiting for better opportunities. This urge to "do something" can lead to impulsive decision making, often at the expense of more deliberate strategic planning (Thaler 2012). In other words, rather than adopting more careful trading strategies, these traders often engage in more frequent and aggressive trading behaviors, such as increasing the volume and frequency of buy and sell transactions. This heightened activity, aimed at quickly recovering their prior status, can paradoxically reduce trading performance due to overtrading or excessive risk taking.

It is important to acknowledge that the cryptocurrency trading market exhibits considerable variability in return rates among traders, owing to the use of leverage and high market fluctuations. Besides, some traders may become inactive after significant gains or losses. To account for these dynamics, we perform analyses after excluding outliers and inactive traders, and the results are documented in Online Appendix G. Table G.2 provides qualitatively consistent results, demonstrating a decrease in performance ($\beta_{TreatDec2nd} = -0.032$, $p < 0.05$) and other associated behaviors. In addition, to alleviate the concern that our experimental manipulation would induce a natural change in follower count, we replicate our analyses using the actual change in follower count as the treatment variable. As shown in Online Appendix L, we continue to find consistent results with our main findings.

Furthermore, mirroring the approach in Section 5.1, we employ the trader-week panel data set to gain a comprehensive understanding of the treatment's effect size. The results, presented in Online Appendix C (Table C.2), reveal that the decreased audience size treatment leads to an average weekly return rate reduction of −1.6% compared with the control group. Additionally, we introduce a continuous treatment

Table 12. Regression Results on Number of Positions in the Second Treatment Phase

	Dependent variable = *NumPositions2nd*		
	(1)	(2)	(3)
TreatInc2nd	0.768 (0.698)	1.558*** (0.435)	1.184*** (0.400)
TreatDec2nd	0.944 (0.682)	3.015*** (0.446)	2.047*** (0.396)
Constant	30.019*** (0.482)	27.954*** (0.304)	28.919*** (0.278)
Groups of subjects	1 to 3	5 to 7	1 to 3, 5 to 7
Observations	4,194	4,896	9,090

Note. Robust standard errors are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 13. Regression Results on Win Rate in the Second Treatment Phase

	Dependent variable = *WinRate2nd*		
	(1)	(2)	(3)
TreatInc2nd	−0.019*** (0.007)	−0.005 (0.004)	−0.012*** (0.004)
TreatDec2nd	−0.010 (0.006)	−0.008** (0.004)	−0.008** (0.004)
Constant	0.444*** (0.005)	0.494*** (0.003)	0.471*** (0.003)
Groups of subjects	1 to 3	5 to 7	1 to 3, 5 to 7
Observations	4,194	4,896	9,090

Note. Robust standard errors are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

variable, $TreatFollowerChangeRatio_t$, to track the weekly change ratio in followers attributed to the treatment intervention. The findings, documented in Online Appendix D (Table D.3), indicate that hypothetically losing all followers (a 100% decrease) in a week is associated with an average 11.1% decline in performance ($\beta_{Treat1st} = -0.111$, $p < 0.01$). These supplementary analyses collectively provide the magnitude of the effect caused by the loss of social audience size.

We also present the estimated coefficients of *TreatInc2nd* to complement our interpretation of the effect size associated with increased social audience size, building on the analyses in Sections 5.1 and 5.2. As anticipated, our findings indicate that heightened social audience size continues to influence traders' behavior. Specifically, increased audience size corresponds to a propensity among traders to utilize higher leverage (column 3 of Table 11, $\beta_{TreatInc2nd} = 0.144$), initiate a greater number of positions (column 3 of Table 12, $\beta_{TreatInc2nd} = 1.184$), and achieve lower win rates (column 3 of Table 13, $\beta_{TreatInc2nd} = -0.012$) and return rates (column 3 of Table 10, $\beta_{TreatInc2nd} = -0.079$).

Although the average effects of increased audience size appear somewhat smaller and less statistically significant, it is important to consider the dynamics of the follower base in interpreting these results. For instance, consider a trader in Group 2 who initially had one follower at the outset of the first experimental phase. During the first phase, assuming no natural follower change, she would receive one additional follower each week, resulting in observed follower change rates of 100%, 50%, 33.3%, and 25%. However, in the second phase, her observed follower change rates decreased to 20%, 16.7%, 14.3%, and 12.5% when there was no natural follower change. Therefore, when examining the effect size of the continuous treatment variable in Online Appendix D2 (Table D.2), doubling the audience size is associated with a substantial −19.7% reduction in return rates. This effect size surpasses that observed in the initial phase (−8.4% from Table D.1). Additionally, considerations regarding the potential inactivity of traders over time should be considered. After addressing these factors, our estimates, as presented in Table G.2 of Online Appendix G, consistently indicate a robust decrease in return rates attributed to increased social audience size (−3.2%). Lastly, we investigate whether social audience size has less impact on experienced traders because they may be less sensitive to such changes. Specifically, we define experienced traders as those whose tenure is in the top 10% of all traders. As shown in Online Appendix O, we find that the effect is indeed insignificant on the trading performance of experienced traders. This further extends our findings and provides a more comprehensive understanding of the impact of social audience size.

All our findings consistently underscore the substantial impact of increased or decreased social audience size. Importantly, the data indicate that traders are motivated to win the lost followers back by trading more aggressively. It suggests that a decrease in social audience size does *not* counteract the effects of increased audience size, aligning with our theoretical framework that posits social audience size as a reference point. It appears that traders who acquire heightened audience size during the first phase establish a new reference point. Consequently, when their audience size declines below this reference point in the second phase, these traders are inclined toward adopting more aggressive trading strategies in an attempt to recover the lost audience. Note that in Tables 10–13, the coefficients of *TreatDec2nd* are generally larger than those of *TreatInc2nd*, indicating a stronger effect when followers are removed. This finding provides suggestive evidence supporting the proposed reference point effect. These insights also serve as a catalyst for our forthcoming exploration of the underlying mechanisms, as detailed in the subsequent section.

6. Mechanism Exploration

In this section, our investigation centers on two key aspects: the presence of overconfidence and the establishment of a reference point. Within our conceptual framework, we have posited that the influence of increased social audience size may come from overconfidence. In such a context, it is plausible to hypothesize that the effect could be more pronounced among traders who exhibit strong performance before acquiring audiences, as they may attribute the influx of audience size to their success in trading.

We test this mechanism leveraging the trader-week level panel data during the first experiment phase. We construct a binary variable, $ReturnRatePosLast_{ut}$, that equals one for the trader u with a positive return rate in dollars in the last week t (i.e., $ReturnRate_{u(t-1)} > 0$) and zero otherwise. In Equation (4), we interact $ReturnRatePosLast_{ut}$ with the treatment indicators ($TreatInc_{ut}$). The outcomes of interest are all the trading performance and behavior measures for trader u during week t.[9]

$$\begin{aligned} Outcome2nd_{ut} = {} & \beta_0 + \beta_1 TreatInc_{ut} + \beta_2 ReturnRatePosLast_{ut} \\ & + \beta_3 ReturnRatePosLast_{ut} \times TreatInc_{ut} \\ & + T_t + \epsilon_{ut} \end{aligned} \tag{4}$$

In Table 14, we are interested primarily in the interactions between the treatment indicators and $ReturnRatePosLast_{ut}$. We find that traders who obtain positive returns in the last week are more affected by increased social audience size than traders who have nonpositive returns in the last week. Specifically, in response to increased audience size in the second phase, the traders with positive first-phase returns open significantly more positions ($\beta_{ReturnRatePosLast \times TreatInc} = 0.715$, $p < 0.01$) with significantly higher leverage ($\beta_{ReturnRatePosLast \times TreatInc} = 0.329$, $p < 0.01$), and they have significantly lower win rates ($\beta_{ReturnRatePosLast \times TreatInc} = -0.010$, $p < 0.1$) and return rates ($\beta_{ReturnRatePosLast \times TreatInc} = -0.040$, $p < 0.01$) than the traders with nonpositive returns in the previous week. We also reported the results with a continuous moderator in Online Appendix Q, showing consistent findings. These results are consistent with our hypothesis that increased social audience size affects traders by inducing overconfidence. We reason that traders who gain audience size and positive financial returns simultaneously are more likely to interpret the new followers as evidence of their skill as traders, leading to overconfidence.

Drawing on prior research related to the reference point theory, it is suggested that traders may assign importance to the digit magnitude of specific values (i.e., round-number bias) (Chen 2018, Hervé and Schwienbacher 2018). As an illustration, consider a scenario where a trader exhibits a heightened inclination to purchase a stock. This inclination may be particularly pronounced when the price undergoes a decrease from 100 (a three-digit value) to 99 (a two-digit value). In the context of this research, if traders indeed use the social audience size (quantified by follower counts) as a reference point, a more pronounced change in their behavior is anticipated when a decline in follower numbers results in a decrease in the digit magnitude of these counts. Consider a scenario where a trader begins with 100 followers. A decline in follower numbers signifies a reduction in this count. For instance, the count might decrease to 98 followers. In this case, the decline in follower numbers leads to a decrease in the digit magnitude, transitioning from three digits to two digits. To explore this premise, we conducted an analysis using the full data sample, focusing on the effects of changes in the digit magnitude of follower counts, the results of which are presented in Table 15. *FollowerDigitDec* is a dummy variable indicating whether the trader experiences a drop in the digit magnitude of follower counts due to the treatment. The findings indicate that after the decreased audience size treatment, a drop in the digit magnitude of follower counts can cause more aggressive trading behavior and a lower return rate ($\beta_{FollowerDigitDec \times TreatDec} = -0.046$, $p < 0.05$). This observation lends empirical support to the theory that social audience size can indeed function as a reference point in the behavior of traders. In addition to the empirical evidence, we conducted supplementary interviews with representative traders from the social trading platform to further support our exploration of the underlying mechanism. Complete details of these interviews can be found in Online Appendix J.

Table 14. Regression Results on the Moderating Effect of Past Trading Performance

	Dependent variable			
	$ReturnRate_{ut}$ (1)	$AverageLeverage_{ut}$ (2)	$NumPositions_{ut}$ (3)	$WinRate_{ut}$ (4)
$TreatInc_{ut}$	−0.014* (0.008)	0.348*** (0.046)	0.858*** (0.068)	−0.016*** (0.004)
$ReturnRatePosLast_{ut}$	−0.001 (0.011)	0.297*** (0.060)	0.577*** (0.087)	0.036*** (0.005)
$ReturnRatePosLast_{ut} \times TreatInc_{ut}$	−0.040*** (0.013)	0.329*** (0.069)	0.715*** (0.103)	−0.010* (0.005)
Constant	0.047*** (0.008)	3.446*** (0.047)	7.124*** (0.069)	0.455*** (0.004)
Groups of subjects	1 to 8	1 to 8	1 to 8	1 to 8
Week fixed effect	Yes	Yes	Yes	Yes
Observations	48,000	48,000	48,000	48,000

Note. Robust standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 15. Regression Results on the Effect of Digit Magnitude Decrease in Follower Count

	Dependent variable			
	$ReturnRate_{ut}$ (1)	$AverageLeverage_{ut}$ (2)	$NumPositions_{ut}$ (3)	$WinRate_{ut}$ (4)
$TreatDec_{ut}$	−0.013* (0.008)	0.241*** (0.043)	0.432*** (0.068)	−0.011*** (0.003)
$FollowerDigitDec_{ut} \times TreatDec_{ut}$	−0.046** (0.023)	0.771*** (0.129)	1.471*** (0.219)	−0.005 (0.008)
Constant	0.064*** (0.008)	3.261*** (0.046)	7.431*** (0.074)	0.444*** (0.004)
Groups of subjects	1, 3, 5, 7	1, 3, 5, 7	1, 3, 5, 7	1, 3, 5, 7
Week fixed effect	Yes	Yes	Yes	Yes
Observations	24,564	24,564	24,564	24,564

Note. Robust standard errors are in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

7. Conclusions and Discussion

Although social trading platforms are growing rapidly and garnering tremendous attention, little is known about the effects of social audience size on traders who share their trading activities on these platforms. Our study empirically examines the impact of social audience size on trading performance and behaviors, and we use overconfidence and the reference point effect as theoretical lenses that may explain the underlying mechanisms. We reported a field experiment conducted on a leading social trading platform that focuses on cryptocurrencies. Specifically, artificial accounts were introduced to "follow" or "unfollow" traders each week, thereby manipulating the audience size they received. First, we find that increased audience size led to worse performance as traders opened more positions and used higher leverage while achieving a lower win rate, which indicates a higher level of overconfidence. The negative effects were stronger among traders who performed well prior to the increase in audience size, consistent with the proposed mechanism of overconfidence. Second, we find that the decrease in audience size did not reverse the original effects of increased audience size. Rather, the decrease in audience size (from traders who previously experienced an increase in audience size) still led to negative performance and more risky aggressive behaviors than the increased audience size did. In addition, there are additional negative effects caused by a decrease in the digit magnitude of follower counts, consistent with the proposed mechanism of social audience size as a reference point.

7.1. Theoretical and Managerial Implications

Our work has important implications for both research and practice. From a theoretical perspective, our study makes an incremental contribution to the broad literature on FinTech. Although prior studies provide important insights into the use of social trading platforms (Oehler et al. 2016), they focus mainly on followers who subscribe to learn about others' trading decisions (Sui and Wang 2022, Deng et al. 2024), with less attention given to the traders who are followed. To the best of our knowledge, our study is the first to empirically examine the dynamic effects of social audience size on traders' trading performance and behaviors on social trading platforms. We find empirical support that the increased audience size may induce overconfidence, and the decrease in social audience size may involve a reference point effect; both types of changes in audience size lead to riskier trading behaviors and worse performance. These results demonstrate the value of using fine-grained data sets to develop a holistic understanding of users' engagement on social trading platforms, especially as social trading has become more influential in the financial market.

This study also adds value to the social media research on the activity of users in large online social networks (Qiu et al. 2018). As many studies have examined the effects of various factors on users' motivation to share and contribute (Zhang and Zhu 2011, Toubia and Stephen 2013, Qiu and Kumar 2017, Qiu et al. 2021), we highlight that more efforts (or higher motivation) do not guarantee more desired outcomes in certain circumstances. More interestingly, we are among the first to evaluate the reversibility of the factor at play. Our two-phase randomized experiment provides causal evidence that the effects of increased audience size are not reversible, consistent with our hypothesis that traders may view social audience size as a reference point.

From a managerial perspective, our study offers important implications for the design of social trading platforms, where traders are the primary knowledge sharers. Because traders may be affected by increases in social audience size, platforms could de-emphasize changes in audience size. Methods such as delaying follower count updates (e.g., several hours or one day), implementing silent periods during critical trading times, or employing alternative indicators like badges or follower categories could mitigate the direct influence of follower counts on trading decisions. These strategies not only foster healthier user interaction but also help shield users from the psychological impacts of fluctuating follower numbers, such as making riskier trades to regain lost followers. In addition, for traders who experienced recent trading losses, platforms could provide tips about the risks of unwise overtrading. Our results also highlight the need for social trading platforms to further understand how external social factors affect traders' performance and behaviors. For example, when launching a new social feature, managers of the platforms should consider whether the introduction of social factors could have overall negative consequences. Last but not least, because the impact of followers on these platforms extends beyond traditional social media dynamics, potentially leading to adverse outcomes for traders, we recommend that policymakers should actively work to curtail the influence of fake followers and penalize deceptive practices.

7.2. Limitations and Future Research Directions

Our research is not without limitations. One limitation of our study is that our results relate to a specific research context, cryptocurrency trading, which might contribute to the large effect size observed in this study. First, the cryptocurrency market is highly volatile and allows 24/7 trading (Nimalendran et al. 2025), leading to potentially large fluctuations in traders' return rates affected by the impact of social audience size. Second, despite the anonymity of the environment, the platform's notification system, which alerts traders to new followers, may reinforce the effect of audience size. Even though traders operate anonymously, the notification system makes them aware of an audience for their actions. In our interviews with a representative sample of traders, detailed in Online Appendix J, all interviewees indicated that they were aware that their followers would be notified of their trading activities, making them feel observed despite the anonymous setting. In addition, because the experiment was conducted by the company, we have no control over the experimental and data generation process. Lastly, our sample primarily consists of traders who opt to disclose their trading activities, possibly indicating a predisposition toward valuing social audience size. We acknowledge this and emphasize that our study specifically focuses on the social trading platform context, a domain of increasing relevance and significance in the financial domain.

However, the platform we study is one of the largest social trading platforms in the world and may be representative of other similar platforms. Specifically, our results can be generalized to other social trading platforms for the following reasons. First, key features of social trading, such as sharing trading activities and the dynamics of followership, are prevalent across various platforms, including those focusing on stock trading. The impact of social audience size on trading decisions is a fundamental aspect of all social trading platforms. Second, financial trading activities, such as opening or closing positions and using leverage, are likely to be similar across different platforms, regardless of the traded asset. Although it is true that cryptocurrency markets may exhibit higher levels of uncertainty and audience size dynamics, these characteristics are also present, albeit to varying degrees, in other financial markets. Additionally, many renowned social trading platforms facilitate trading in diverse financial assets, including cryptocurrencies. Third, cryptocurrency trading is increasingly popular among traders in financial markets (Ilk et al. 2021, Petryk et al. 2023). According to eToro,[10] the leading multiasset trading platform Bitcoin is the most common investment, accounting for 1 of every 25 opened positions. In addition, we realize that there are some data limitations in our empirical study. For example, we lack detailed demographic information, so we could not examine heterogeneous treatment effects among different groups of traders. Also, we could not measure how much each trader cared about social audience size. Future research may use clickstream-level data to determine whether the effects of increased/decreased audience size are more substantial among traders who click more often on social features.

It is important to acknowledge that this study's capacity to elucidate the underlying mechanisms may be constrained, as direct observation of traders' cognitive processes during transaction execution remains inaccessible. Besides, our focal traders are those who choose to disclose their trading activities, which may heighten their sensitivity to follower counts. However, given our focus on the trader's side and the increasing prominence of social trading platforms, we believe our findings on the impact of social audience size on trading performance and behaviors can be generalized to similar social trading contexts. Future studies may explore the followers' side as a research direction (i.e., users who do not disclose their trading activities but follow other traders).

In addition, although our study primarily examines the negative effects of social audience size on a specific metric, namely, the performance of the traders being followed, a larger audience can also positively influence other metrics. For instance, an increase in followers may attract new users to the social trading platform, thereby contributing to platform growth and enhanced community interaction. Additionally, a larger social audience can encourage traders to share valuable insights and strategies, fostering a collaborative environment for knowledge exchange. Importantly, following can also benefit followers, as they may learn from experienced traders by observing their strategies, leading to improved decision making and performance (Apesteguia et al. 2020, Shen et al. 2022). Although these aspects are not covered in the current study, future research could explore these potential positive impacts more thoroughly. Another area of future research could focus on how the engagement of followers influences trader retention and long-term success on the platform.

Our work can be extended in several ways. First, given our finding of negative consequences of social audience size, it may be valuable to design (and empirically test) social features to boost engagement without affecting traders' performance and behaviors. Second, some social trading platforms allow subscribers to copy the trades of experienced traders, who receive monetary compensation for sharing their activities. It would be interesting to examine how the interaction between monetary incentives and social audience size affects traders' performance and behaviors. Third, despite our findings on the negative impact of social audience size, it does not necessarily mean that everyone will be worse off in social trading. Top traders are capable of generating profits early on, and as they attract more followers due to their exceptional performance, they may experience various changes. However, these top traders can still maintain positive earnings. As their audience size grows to a certain level, they may become more accustomed to these fluctuations, and the impact of such changes might be relatively smaller due to their large follower base. In contrast, less outstanding traders may initially earn profits and gain followers, but once they acquire a following and are influenced by it, they may struggle to sustain high performance or may even begin to incur losses, which leads to a loss of followers and initiates a "death spiral." Future studies may look into the long-term dynamics equilibrium of these traders. Finally, our research only examines the effects of social audience size from a static perspective. Future research can be performed to further investigate whether the influence of social audience size is transmitted under the follower-followee network. For example, the propagation of social audience size may promote a more aggressive trading style within the whole online community.

Endnotes

[1] See https://finance.yahoo.com/news/etoro-reports-fourth-quarter-full-142600526.html (Yahoo! Finance, accessed July 1, 2022).

[2] We also conducted interviews with representative traders who indicated that they are attentive to the number of followers they have. Additional details can be found in Online Appendix J.

[3] The experiment was directly conducted by the company, and we obtained experimental data for analysis.

[4] More details about the platform are disclosed in Online Appendix K.

[5] We choose the median value to ensure the consistency of the treatment so that different groups in the experiment are comparable. In addition, it can sufficiently affect the behavior of traders in each group. Note that it is not exactly 1,500 because of the median split and the randomization system that assigns each trader to a random group independently.

[6] We also calculate the return rate based on the number of BTCs ($ReturnRateBTC1st_u$), the details of which are provided in Online Appendix B.

[7] We include the win rate as an indicator of behavior rather than performance because the win rate reflects the quality of the trader's decisions, which provides insight into risk preferences, aggressiveness, and overconfidence.

[8] Again, we also calculate the return rate based on the number of BTCs ($ReturnRateBTC1st_u$), the details of which are provided in Online Appendix B.

[9] We omit the covariates $ReturnRate1st_u$ and $ReturnRateBTC1st_u$ because we use the dummy variable $ReturnRatePos1st_u$ here. For parsimony, we display only the results of the return rate in dollars and only the results of Equation (6). For the omitted results, see Online Appendix A (Table A.3 and Table A.4).

[10] See https://www.etoro.com/news-and-analysis/etoro-updates/20m-users/ (eToro, accessed July 4, 2022).

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