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How Financial Influencers Rise: Performance Following and Social Transmission Bias[1]

By **Shixiang Cao, Zhigang Qiu, Xinyi Shao and Ke Song**[*]

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Abstract

Using unique account-level data from a leading Chinese fintech platform, we investigate how financial influencers, the key information intermediaries in social finance, attract followers through a process of social transmission bias. We document a robust performance-following pattern wherein retail investors overextrapolate influencers' past returns rather than rational learning in the social network from their past performance. The transmission bias is amplified by two mechanisms: (1) influencers' active social engagement and (2) their index fund-heavy portfolios. Evidence further reveals influencers' self-enhancing reporting through selective performance disclosure. Crucially, the dynamics ultimately increase risk exposure and impair returns for follower investors.

Key Words: Financial Influencers; Retail Investors; Social Transmission Bias; Fintech Platform

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[*] The authors acknowledge and appreciate the supports from the Digital Economy Open Research Platform (www.deor.org.cn). All data is sampled, desensitized, and stored on the Ant Open Research Laboratory in an Ant Group Environment which is only remotely accessible for empirical analysis.

A missing chapter in our understanding of finance consists of the social processes that shape economic thinking and behavior.

——DAVID HIRSHLEIFER (2020)

1. Introduction

The influence of social networks on investor decision-making has been well-documented (e.g., Hong, Kubik and Stein (2004); Brown, Ivković, Smith and Weisbenner (2008); Hirshleifer (2020)), with recent research increasingly focusing on the role of online social media and fintech platforms in information production and dissemination (e.g., Cookson, Engelberg and Mullins (2023); Barber, Huang, Odean and Schwarz (2022); Hong, Lu and Pan (2019)).[2] Notably, financial influencers — individuals with significant social media followings — have emerged as pivotal actors on fintech platforms (e.g., Stock Twits), where they shape information flows and wield substantial market influence (Kakhbod, Kazempour, Livdan and Schuerhoff (2023)). Functioning as authoritative yet informal information sources, the impact of financial influencers rivals traditional intermediaries while potentially amplifying retail investors' behavioral biases and market irrationality, ultimately raising concerns about market efficiency and investor welfare (Pedersen (2022)).[3]

The rise of financial influencers as key information intermediaries reveals a critical literature gap, as existing research has primarily focused on general investment information diffusion in social networks (Apesteguia, Oechssler and Weidenholzer (2020); Ammann and Schaub (2021)) while neglecting how financial influencers accumulate their informational authority. Financial influencers serve as central nodes in market information networks, critically determining information breadth and impact, yet the mechanisms through which they build such influence remain relatively underexplored. Conventional wisdom maintains that investors primarily follow influencers based on their demonstrated performance and observable social behaviors. However, we may have competing theoretical frameworks: rational learning posits Bayesian belief updating progress based on information inferred from their social network (Acemoglu, Dahleh, Lobel and Ozdaglar (2011)) whereas behavioral perspectives highlight social transmission biases like return overextrapolation (Han, Hirshleifer and Walden (2022)).[4]

Using proprietary transaction data from Ant Fund, a leading Chinese fintech platform, we examine the dual mechanisms governing financial influencer emergence: (1) the determinants of retail investor following behaviors, and (2) potential behavioral biases in social information diffusion. Our analysis reveals a performance-following pattern in

[2] In the Internet Era so called "Web 2.0", information production is similar to data production (Goldstein, Spatt and Ye (2021)). For example, the opinions posted by financial influencers are also regarded as one types of big data, which can be regarded as the process of information production.

[3] Moreover, anecdotal evidence suggests that some financial influencers may use their popularity to spread rumors, mislead investors, and even engage in illegal profit-making activities. For example, the China Securities Regulatory Commission regularly discloses individuals or institutions that spread false information.

[4] The dependence of investors' following behavior on past performance mirrors well-documented patterns in the mutual fund industry. As Berk and Green (2004) demonstrate, retail investors routinely infer managerial skill from historical returns when evaluating mutual funds - a cognitive process strikingly similar to how social media followers assess financial influencers.

influencer formation, wherein investors exhibit a marked preference for traders with conspicuous short-term returns over those with demonstrated sustainable investment skills. This pattern suggests investors systematically extrapolate attention-grabbing performance signals. Moreover, we provide robust evidence that such social transmission biases significantly distort the process of influence accumulation in financial markets.

Our data reveals several distinctive characteristics of financial influencers on the fintech platform. First, while financial influencers represent a small fraction (0.48%) of individual investors, their influence remains relatively limited in scope — only 30.1% attract more than 1,000 followers, and a mere 9.8% surpass 3,000 followers. Second, these influencers distinguish themselves through active platform engagement, regularly sharing investment-related contents including portfolio holdings and trade executions, while strategically choosing whether to disclose their performance outcomes. Third, and most notably, summary statistics show that the raw returns and risk-adjusted returns of financial influencers are both negative, indicating that influencer status does not necessarily correlate with superior investment capability or distinctive traits.[5]

Our empirical investigation begins by addressing a core question: what factors drive retail investors to follow specific financial influencers? The baseline analysis reveals a robust performance-following relationship in which influencers' past investment returns show a statistically significant positive association with their follower growth. This finding persists across multiple model specifications and remains significant after controlling for both asset characteristics and platform-level network features, indicating that the observed relationship is not merely an artifact of recommendation algorithms.

We next examine whether the performance-following relationship stems from social transmission bias or rational learning in the social network. Our empirical evidence robustly supports an overextrapolation hypothesis, revealing that retail investors systematically misinterpret short-term performance salience as persistent managerial skills. In line with Da, Huang and Jin (2021), we find that salient returns, particularly the maximum-return fund within an influencer's portfolio, attract disproportionately large retail investors follows. This behavioral pattern becomes institutionally embedded through the platform's interface design that enables influencers to selectively highlight top-performing assets. Our findings extend the framework proposed by Han, Hirshleifer and Walden (2022), highlighting a feedback mechanism where visibility, rather than informational value, drives influence accumulation.

In contrast, rational social learning predicts Bayesian belief updating, in which reduced signal noise hastens belief convergence. Our findings, however, contradict this prediction: investors disproportionately favor influencers exhibiting higher intra-month volatility and cross-fund return dispersion, while remaining indifferent to return persistence. Notably, attention flows are driven solely by recent performance, with longer-term track records

[5] In our study, financial influencers are defined as social platform investors with over 100 followers at the end of December 2023. These operational definitions distinguish influential users from general investors based on measurable social engagement metrics.

proving irrelevant — a pattern that aligns precisely with models of imperfect recall (Molavi, Tahbaz Salehi and Jadbabaie (2018)). Collectively, our findings challenge the predictions of Bayesian learning and point instead to a salience-driven extrapolative tendency, shaped by both investor attention and the presentation structure of social investment platforms.

Building on confirmation of behavioral explanation, we further examine the amplification mechanisms of overextrapolation bias. First, the performance-following relationship strengthens markedly when influencers generate high returns through index funds, probably because these investments represent particularly salient performance signals. Intuitively, the strong performance of index fund investments may signal an influencer's sector-specific investment acumen, allowing for more direct performance attribution than actively managed funds. Second, the behavioral bias is significantly more pronounced among frequent content posters, indicating that active platform engagement serves to reinforce investors' tendency to overextrapolate from past returns.[6]

To elucidate how posting behavior amplifies influence, we analyze financial influencers' strategic disclosure patterns in social interactions. Building on impression management theory (e.g., Chen and Hwang (2022)) and information transmission model (e.g., Han, Hirshleifer and Walden (2022)), we document a self-reinforcing cycle: (1) higher returns significantly increase influencers' likelihood of sharing opinions, and (2) this selective disclosure of positive performance further strengthens the performance-following relationship. These strategic posting behaviors create an asymmetric information flow that systematically amplifies investors' performance extrapolation bias.

Finally, we provide empirical evidence that retail investors who follow financial influencers experience notably poorer investment outcomes, exhibiting depressed returns while simultaneously increasing their allocations to both index funds and high-volatility securities in subsequent periods. These results indicate that the performance-following behavior induced by overextrapolation bias leads to systematically suboptimal portfolio decisions, revealing the limitations of social media following as a viable information acquisition strategy in financial markets.

Our paper contributes to the growing literature on social media (e.g., Blankespoor, Dehaan, Wertz and Zhu (2019); Han and Yang (2013); Tumarkin and Whitelaw (2001)), in which participants produce and disseminate information.[7] Due to data limitations, early papers in this field use indirect measurements of social interaction for investors' behavior (e.g., Hong, Kubik and Stein (2005); Brown, Ivković, Smith and Weisbenner (2008), Kaustia and Knüpfer (2012)). In recent years, researchers have been able to obtain data directly from online platforms and observe the behavior of platform

[6] For example, Hong, Lu and Pan (2019) suggests that the concentration of information flow and product distribution on Fintech platform amplifies the sensitivity of fund flows and past performance.

[7] The advent of social media such as Twitter, has significantly improved the efficiency of information dissemination (e.g., Bartov, Faurel and Mohanram (2022); Blankespoor, Miller and White (2014)) and provided investors with cost-effective insights (e.g., Antweiler and Frank (2004)).

participants. For example, Bali, Hirshleifer, Peng and Tang (2021) find that social interaction on Facebook increases investors' attraction to lottery stocks, and Farrell, Green, Jame and Markov (2022) find that social interaction on Seeking Alpha increases informativeness of retail trading. Our paper focuses on one of the most important groups of participants on social media, namely financial influencers, complementary to literature.

We also contribute to the literature of social transmission bias (e.g., Hirshleifer (2020)), with a special focus on the financial influencers' behavior to attract followers. Financial influencers play an important role of information production and dissemination in the social interaction community (e.g., Pedersen (2022)), and the online information acquisition has significant impacts on investors' decision making (e.g., Apesteguia, Oechssler and Weidenholzer (2020); Ammann and Schaub (2021); Deng, Yang, Pelster and Tan (2023)). However, as pointed out by Han, Hirshleifer and Walden (2022), there may be behavioral bias in the information transmission between financial influencers and retail investors. For example, using Seeking Alpha's log data, Chen and Hwang (2022) find that investors shares more articles which can help them do impression management, and Kromidha and Li (2019) argue that qualifications are more important for leadership of online trading. Our paper uses the unique data from Ant Fund to closely analyze how financial influencers attract followers, which helps deepen our understanding of information transmission mechanisms.

Finally, our paper is closely related to Sui and Wang (2022), as both provide empirical evidence on social transmission bias. However, our study differs in several important respects. First, while Sui and Wang (2022) examine how influencers' posts affect followers' trading behavior after the social network has been established, we focus on the overextrapolation bias that shapes influencers' ability to attract new followers during the network formation stage. Second, our analysis centers on information diffusion and investment behavior in the mutual fund market, whereas Sui and Wang (2022) investigate stock trading decisions in the context of direct equity investment.

The remainder of the paper is organized as follows. In Section 2, we provide the background of the fintech platform and financial influencers. In Section 3, we describe the data and variables. Section 4 analyzes the performance-following relationship and overextrapolation bias, and how the overextrapolation bias is amplified is discussed in Section 5. Section 6 examines the real impacts of behavioral bias on retail investors, and Section 7 concludes. Variable definitions are presented in Appendix A.

2. Institutional background

2.1 Fintech platform

Fintech platforms have become the primary channel for individual investors in today's financial markets, with leading examples including Snowball and East Money. Our study examines Ant Fund, one of China's largest fintech platforms operated by Ant Group, which specializes in mutual fund distribution.

Ant Fund platform offers investors comprehensive access to China's mutual fund market, featuring diverse products such as bond funds, equity funds, index funds, hybrid funds, ETF-linked funds, QDII funds, and FOF funds.[8] In addition, it provides limited access to other financial products including insurance and gold. A distinctive feature of Ant Fund is its integrated online financial community — resembling a financial version of Twitter — where retail investors can exchange ideas and share market insights.

2.2 Investor community[9]

The Ant Fund APP features an investor community that serves as an interactive platform for discussing investment strategies and market trends. This online space connects individual investors with fund companies and managers through multiple engagement channels, including following, liking, posting, and sharing. Notably, participation requires no prior investment on the platform, all users can freely express their views. Similar to mainstream social media, the platform delivers personalized financial content and advertisements to all users, even those who do not follow specific accounts. The community primarily consists of Chinese investors communicating in Chinese. Content creation is unrestricted in terms of format (text, emojis, images, videos) or length. Discussions predominantly focus on financial topics, particularly market analysis and investment strategies.

2.3 Financial influencers

According to social interaction theory, financial influencers — often referred to as financial opinion leaders — play a pivotal role in information diffusion and exert substantial influence on user decision-making (e.g., Zhao, Kou, Peng and Chen (2018)). These influencers predominantly disseminate their perspectives through financial social media platforms.

Figure 1 displays a typical financial influencer profile on Ant Fund. The platform enables influencers to share investment strategies, analyze markets, recommend products, and engage with investors. Each profile includes key tags, IP location, personal bio, and engagement metrics (followers/likes). Investors must subscribe to access the influencer's complete trading history and posts, making this the primary channel for obtaining influencer-generated content.

Figure 1. The introduction of financial influencer

Figure 1 provides screenshots of the App user interface. The left figure is the user interface when people are browsing the social platform section in the App. After clicking

[8] Ant Fund, a leading large-scale Fintech platform provided by Ant Group. Established in 2007, Ant Fund is an online wealth management platform under Alipay. It collaborates with financial institutions to provide wealth management services, offering various products such as mutual funds, wealth management products, and insurance. According to data from the Asset Management Association of China (AMAC), Ant Fund was ranked as the second largest sales agency for mutual funds in 2021, with 571.9 billion RMB equity fund holdings.

[9] Ant Fund has developed various wealth management services for retail investors. First, it is a comprehensive wealth management platform that enables investors to purchase products through Alipay accounts. More important, Ant Fund has established a social interactive community in which individual investors and financial institutions can share ideas and opinions. On Ant Fund, investors can obtain useful information through various social media channels, including news, posts, videos, live broadcasts, and interactive Q&A. So far, Ant Fund has hundreds of millions of active mutual fund investors with over 400 million visits.

the influencers' profile image, user can go to the influencers' homepage (the right figure). If there's a ticker named "with actual fund holding", it means that the influencer chooses to show his investment performance. Although everyone can browse the summary of an influencer's performance if investors choose to show it, only those people subscribe the influencer can see the detail, which include the actual holding, holding period return and return in the last day of each fund hold by the influencer.

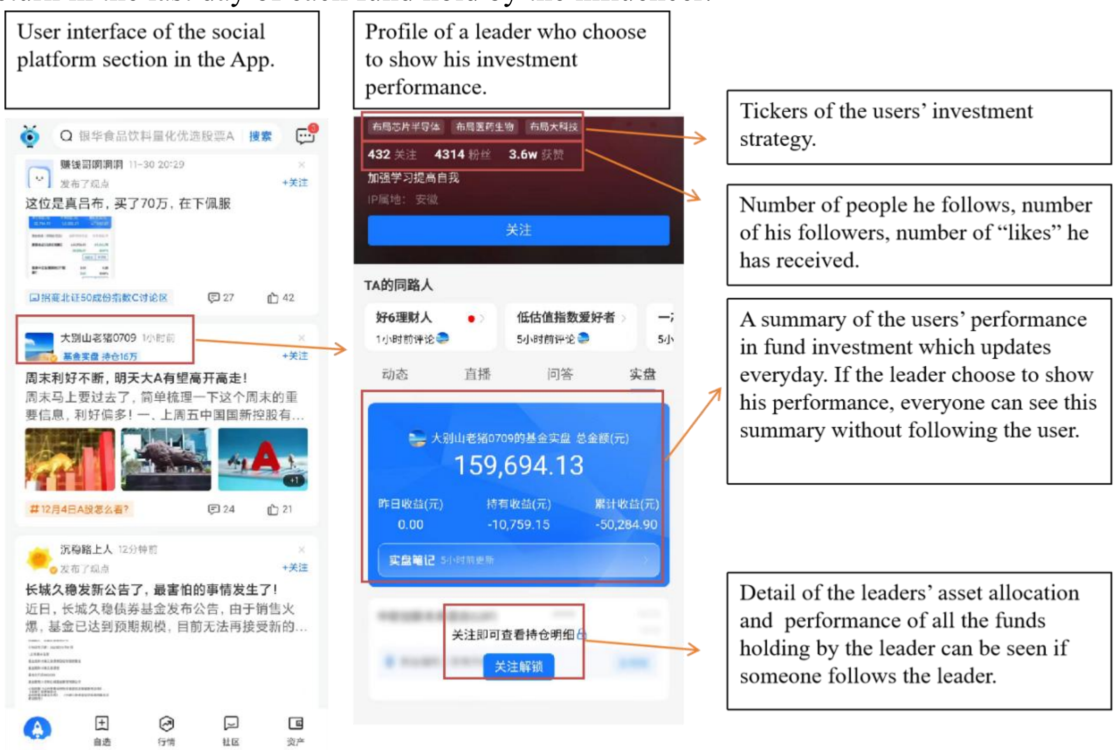


Figure 2 presents a representative post from a financial influencer's homepage, which primarily consists of two types: *holding notes* (Panel A) and *trading notes* (Panel B).[10] Holding notes disclose portfolio holdings and corresponding mutual fund returns, while trading notes describe trading activities and strategies. Both post types include detailed commentary explaining the investment rationale. By sharing these insights, influencers demonstrate their investment approach and performance, fostering follower engagement and potentially attracting new followers.

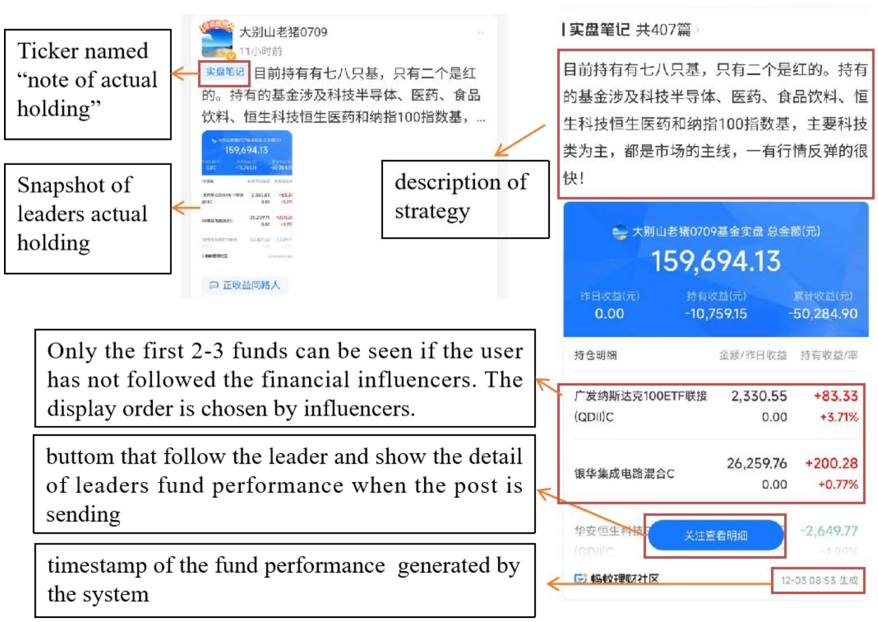
Figure 2. The typical posting of financial influencer

Figure 2 provides screenshots of two special type of posting where financial influencer can show investment strategy and performance in detail. Panel A is a posting with a ticker named "note of mutual fund holding", which provide a chance to see the holding position and investment performance of all the mutual fund holding by the influencer,

[10] According to Ant Fund community guidelines, financial influencers may choose not to disclose their positions and transactions. However, based on casual observation, we observe various disclosure behaviors of financial influencers, possibly because more information disclosure may help them gain more followers.

only those people which subscribes the influencer can browse the detail. Noted that the holding position and performance is generated by the system when the influencer sending the posting and keep unchanged since then, and there's a timestamp recording the generating time. Panel B is a posting with a ticker named "note of mutual fund trading", which provide a recording of all the purchase and redemption on a selected mutual fund by the influencer. Financial influencer can choose which mutual fund to report and everyone can see the record.

Panel A. The note of mutual fund holding by financial influencer

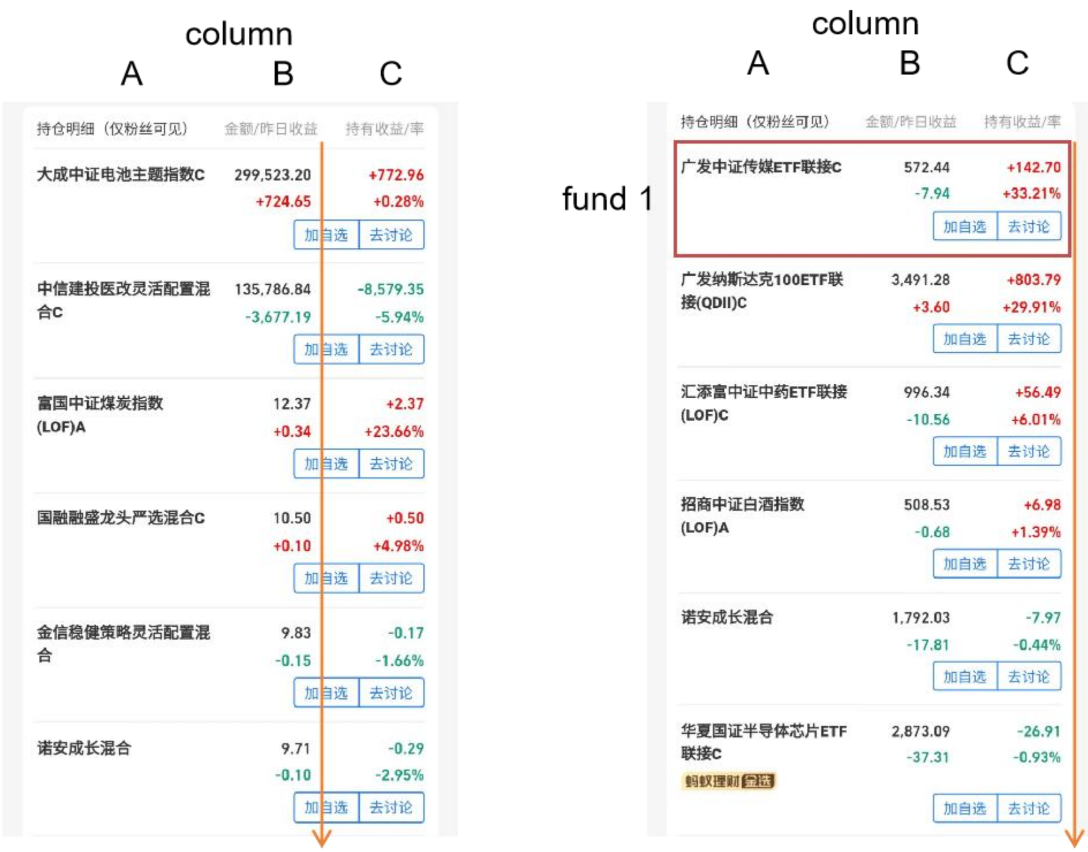


Panel B. The note of mutual fund trading by financial influencer

Financial influencers can strategically present their portfolio allocation by sorting fund holdings either by investment size (shares held) or by performance (returns) in a system snapshot.[11] This selective presentation enables them to highlight either their investment strategy or performance outcomes. Figure 3 illustrates the contrast between these two display methods.[12]

Figure 3. The investment performance of the financial influencer

Figure 3 provides screenshots of the investment performance report provided by the financial influencer. The investment performance report consists of three columns, Column A is the name of the mutual fund, Column B is the position and return of the mutual fund on the last day, Column C is the return during the holding period. There are two ways to present investment performance, the left report is sorted by the position, and the right report is sorted by the return. The way in which the report is sorted is up to the influencer's choice.



3. Data and Variable

[11] The system snapshot feature operates on an opt-in basis, but participating influencers must fully disclose their portfolio holdings to existing followers, while retaining control over the display order of assets. Prospective followers are shown a summary view including total assets, overall returns, and the top two funds in the influencer's chosen ranking. Additionally, influencers can strategically highlight specific investment information through supplementary posts (e.g., portfolio screenshots or textual commentary) to shape their public profile.

[12] In fact, we cannot observe all the homepages of financial influencers in our data. The purpose of this example is to show that if financial influencers want to attract the attention of retail investors, they have a lot of room to adjust the way their posts are displayed.

3.1 Data

Our data comes from Ant Fund and captures the social interactions and investment behaviors of financial influencers, allowing us to closely observe their information acquisition and investment decisions on the Fintech platform. Specifically, we randomly collect detailed information on 9,766 financial influencers and 31,246 retail investors from Ant Fund users, including their monthly information dissemination or reception and investment strategies. We require financial influencers to have at least 100 followers as of the end of December 2023[13]. In order to exclude investors who do not obtain information from the Ant Fund APP, the retail investors sample must have performed at least six following actions and six liking actions within 24 months, with a total reading time on the platform exceeding three hours. The sample period spans from January 2022 to December 2023, comprising 24 monthly periods.[14]

3.2 Variables

Our empirical framework analyzes both financial influencers and retail investors across three fundamental dimensions: information dissemination patterns, investment behaviors, and demographic profiles. Regarding financial influencers, we quantify their information propagation capacity through comprehensive metrics including *Total Followers* and *New Followers*, while assessing their social engagement levels via posting frequency (*Opinions*).[15] The investment profiles are measured by their investment characteristics (returns, holdings, and trading behavior), including one-month return (*Ret_1M*), three-month alpha (*Alpha_3M*), the single best-performing fund (*Ret_Max1*), and that of the most heavily held fund (*Ret_Core1*), gain from trade comparing to a counterfactual no-trading status (*Gain_Trade*), one-month volatility (*Vol_1M*), the ratio of funds with positive returns (*Posret*), portfolio-level variance of fund returns (*Ret_var*), *Total Assets*, the proportion of mutual funds in total assets (*Fund_pct*), the proportion of index funds in fund investments (*Index_pct*). Finally, we collect demographic data on financial influencers, including *Gender*, *Age*, *Risk*, and *APP_Use*.

For retail investors, we focus on their interaction with influencer content through following, reading, and liking behaviors, alongside parallel investment metrics to ensure comparability. For information reception, we use following, reading, and liking behaviors directed toward financial influencers (*Follow_op*, *Read_op*, and *Like_op*) as indicators. The remaining variables are consistent with those used for financial influencers.

All variables are formally defined in Appendix A, ensuring transparency in measurement and replicability.

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[13] In our sample, some financial influencers do not have followers at the beginning of sample period, but eventually have more than 100 followers at the end of sample period.

[14] This study was remotely conducted on the Ant Open Research Laboratory in an Ant Group Environment. The data was sampled and desensitized by the Ant Group Research Institute and stored on the Ant Open Research Laboratory. The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis and individual observations are not visible.

[15] Due to the privacy protection policy of the platform, we are unable to observe the list of followers of financial influencers, nor can we observe which financial influencers individual investors have subscribed to. Therefore, we cannot construct a complete network of financial influencers and their followers.

3.3 Summary statistics

We present the summary statistics for financial influencers and retail investors in Panels A and B of Table 1, respectively.

Panel A reports summary statistics for financial influencers. On average, they have 3,606 followers and gain 75 new followers and post 62 opinions in a month. Their monthly return is -1.03%, which gains an alpha of -0.01% after adjusting for the benchmark return.[16] On average, financial influencers hold 187,319 RMB in total assets, with 69.7% allocated to mutual funds (29.7% of which are in index funds). The cohort averages 34.2 years in age, comprises 31.7% females, and shows median risk tolerance of 3.091 with 9.183 years of average platform experience.

Panel B presents summary statistics for retail investors. On average, they follow 1.134 financial influencers, spend 150.55 minutes per month on the platform, and click the like button about 10 times a month. Their average monthly return is -1.21%, which gains an alpha of -0.39% after adjusting for the benchmark return. Their total asset value is on average 225,284 RMB, mutual funds account for 81.9% of assets, and 35.2% of which are invested in index funds. Retail investors are 40.0 years old on average, 37.9% are female, have a median risk tolerance of 3.262, and use the APP for an average of 10.313 years.

[16] By comparison, the Shanghai Composite Index returned -18.66% over the sample period, corresponding to an average monthly return of -0.72%.

Table 1. Summary statistics

Table 1 presents the summary statistics. Panel A of Table 1 presents the summary statistics of the financial influencers. Panel A of Table 1 presents the summary statistics of the retail investors. The sample period is from January 2022 to December 2023. This table reports characteristics of social interaction, for financial influencers, we report variables related to information dissemination (***Total Followers, New follower, Opinions***); for retail investors, we report variables related to information reception (***Follow_op, Read_op, Like_op***). We also report their investment characteristics (***Ret_1M(%)***
, Ret_Max1(%), Ret_Core1(%), Gain_Trade(%), Alpha_3M(%), Vol_1M(%), Posret, Ret_var(%), Asset, Fund_pct, Index_pct). For each variable. Besides, we present the portrait of financial influencer and retail investor which does not vary over time, including ***Gender, Age, Risk, APP_use***. We report the sample mean **(*Mean*)**, the standard deviation **(*St.dev*)**, and the 1st,25th,50th **(*Median*)**,75th and 99th percentiles. Appendix A explains the variable definition.

Variable Name	***Count***	***Mean***	***Std***	***1%Pct***	***25%Pct***	***Median***	***75%Pct***	***99% Pct***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Summary statistics of financial influencers								
Total Followers	115317	3606.243	19529.608	0.000	155.000	368.000	1032.000	430881.000
New follower	108879	74.566	280.972	0.000	0.000	0.000	6.000	1913.000
Opinions	137287	62.001	208.882	0.000	0.000	0.000	10.000	1299.000
Ret_1M(%)	137287	-1.025	4.832	-14.201	-3.547	-0.534	0.917	12.338
Ret_Max1(%)	137252	4.942	7.598	-10.585	0.178	2.851	9.435	31.231
Ret_Core1(%)	136946	-0.853	5.851	-16.206	-4.009	-0.151	1.1111	15.235
Gain_Trade(%)	129315	-0.091	1.781	-6.215	-0.371	-0.046	0.118	5.988
Alpha_3M(%)	137287	-0.005	0.048	-0.168	-0.021	0.000	0.013	0.164
Vol_1M(%)	137287	1.125	0.696	0.000	0.646	1.171	1.572	2.942
Posret	137287	0.421	0.358	0.000	0.063	0.353	0.722	1.000
Ret_var(%)	111515	4.132	2.482	0.055	2.522	3.768	5.430	12.332
Asset	137287	187,319	407,235	0	1,839	32,996	167,342	2435,844

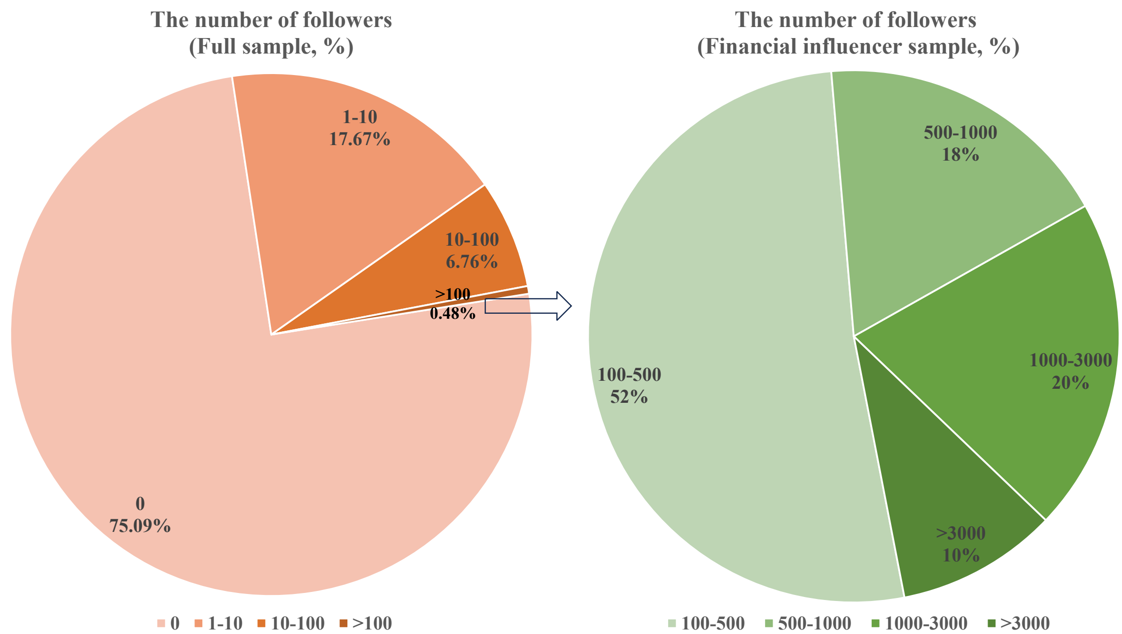
Variable Name	*Count*	*Mean*	*Std*	*1%Pct*	*25%Pct*	*Median*	*75%Pct*	*99% Pct*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fund_pct	136888	0.697	0.358	0.000	0.443	0.884	0.991	1.007
Index_pct	134759	0.297	0.342	0.000	0.000	0.153	0.527	1.005
Gender	9766	0.317	0.465	0.000	0.000	0.000	1.000	1.000
Age	9766	34.169	10.317	18.000	27.000	32.000	39.000	67.000
Risk	9766	3.091	0.940	1.000	2.000	3.000	4.000	5.000
APP_Use	9766	9.183	3.957	1.000	7.000	9.000	12.000	18.000
Panel B: Summary statistics of Retail investors								
Follow_op	716473	1.134	2.529	0.000	0.000	0.000	1.000	16.000
Read_op	747719	150.547	243.244	0.000	11.530	53.243	176.049	1374.443
Like_op	747719	9.880	35.587	0.000	0.000	0.000	3.000	264.000
Ret_1M(%)	747719	-1.214	4.783	-13.664	-3.802	-0.984	0.870	11.672
Gain_Trade(%)	716473	-0.125	1.522	-26.565	-0.392	-0.045	0.163	22.680
Alpha_3M(%)	747719	-0.388	3.273	-11.902	-1.657	0.000	0.909	10.786
Vol_1M(%)	747719	1.266	0.638	0.013	0.942	1.309	1.656	2.833
Asset	747719	225.284	266.181	2.611	69.371	132.646	268.893	1574.316
Fund_pct	747631	0.819	0.243	0.000	0.748	0.928	0.989	1.005
Index_pct	746043	0.352	0.284	0.000	0.100	0.320	0.541	1.006
Gender	31246	0.379	0.485	0.000	0.000	0.000	1.000	1.000
Age	31246	40.013	10.879	23.000	32.000	38.000	40.000	69.000
Risk	31246	3.262	1.079	1.000	2.000	4.000	4.000	5.000
APP_Use	31246	10.313	3.198	4.000	8.000	10.000	12.000	18.000

3.4 Cross-sectional characteristics of financial influencers

Our analysis begins by examining the cross-sectional characteristics distinguishing financial influencers from retail investors (Figure 4 and Table 2, Panel A). Results show influencer status is highly exclusive: only 0.48% of investors exceed the 100-follower threshold. The follower distribution reveals 75.09% have no followers, 17.67% have less than 10 followers, and 6.76% have 10-100 followers. Therefore, the true influencer status is exceptionally rare. For this reason, we focus on accounts with meaningful influence by excluding those below the follower threshold.

Figure 4. The distribution of the followers of financial influencer

Figure 4 shows the distribution of the number of followers for individual investors. The left graph presents the distribution of the number of followers for the full sample (including all investors), while the right graph shows the distribution for financial influencers (those with more than 100 followers). The financial influencers with more than 100 followers (as shown in the right graph) account for only 0.48% of the full sample.



We further classify the 0.48% financial influencers into four categories: small (100-500 followers), medium (500-1000), large (1000-3000), and super (>3000 followers).[17] The distribution shows significant concentration at the lower end: small influencers dominate (51.7%), followed by large (20.3%), medium (18.2%), and super

[17] The impact of financial influencers can be effectively assessed by the magnitude of their follower. We employ Ant Fund's business criteria to classify financial influencers into five tiers based on their follower count.

influencers (9.8%).

Table 2 presents systematic comparisons across influencer categories, revealing several key patterns. First, super influencers demonstrate markedly greater engagement in social media, averaging 275.45 monthly posts — significantly higher than other influencers. Second, investment returns do not differ significantly across influence levels. Third, as influence increases, total assets, the proportion of fund assets, and the share of index funds tend to rise. Finally, demographic characteristics such as age, gender, risk tolerance, and app usage show no substantial variation across groups.

Table 2. Characteristics of financial influencers with different levels of influence

Table 2 presents the summary statistics of follower for the financial influencer. We report the number of followers for the retail investor, and we divide investors into four categories: Small financial influencer (Followers between 100 to 500), Medium financial influencer (Followers between 500 to 1000), Large financial influencer (Followers between 1000 to 3000), Super financial influencer (Followers ≥3000). We present the distribution of financial influencer in Panel A and the difference of financial influencers with different levels of influence in Panel B (*Mean*). Appendix A explains the variable definition.

Number of followers	**100-500**	**500-1000**	**1000-3000**	**>3000**
	Small financial influencer	Medium financial influencer	Large financial influencer	Super financial influencer
	(1)	(2)	(3)	(4)
Panel A. The distribution of financial influencer				
Count	4978	1750	1951	940
Proportion in influencers	51.7%	18.2%	20.3%	9.8%
Proportion in full sample	0.25%	0.09%	0.10%	0.05%
Panel B. The difference of financial influencers with different levels of influence				
Opinion_all	23.401	114.417	56.423	275.453
Ret_1M(%)	-1.017	-1.027	-1.056	-1.041
Ret_Max1(%)	4.845	4.631	4.705	6.415
Ret_Core1(%)	-0.836	-0.865	-0.921	-0.864
Gain_Trade(%)	-0.100	-0.083	-0.064	-0.077
Alpha_3M(%)	-0.005	-0.005	-0.005	-0.005
Vol_1m(%)	1.136	1.093	1.037	1.212
Posret	0.427	0.413	0.406	0.412
Ret_var(%)	4.216	3.734	3.981	4.293
Asset	172.550	158.886	187.312	331.490
Fund_pct	0.690	0.698	0.690	0.758
Index_pct	0.282	0.305	0.318	0.370

Number of followers	**100-500**	**500-1000**	**1000-3000**	**>3000**
	Small financial influencer	Medium financial influencer	Large financial influencer	Super financial influencer
	(1)	(2)	(3)	(4)
Gender	0.280	0.281	0.314	0.259
Age	34.760	35.116	35.704	35.682
Risk	3.223	3.250	3.240	3.466
APP_use	10.104	10.452	9.877	10.534

4. Performance-following relationship and overextrapolation

Ant Fund's investor community relies heavily on informal user posts and influencer networks for information diffusion, which creates a social transmission environment where performance visibility and peer effects may amplify investor reactions. Our analysis reveals that these responses are driven primarily by short-term, high-salience signals rather than persistent skill indicators — consistent with an overextrapolation bias in performance-following behavior.

We analysis reveals a robust performance-following pattern, in which (1) we show baseline evidence of performance-following pattern (Subsection 4.1); (2) we conduct robustness tests by controlling for platform algorithms and other specifications (Subsection 4.2); (3) we further identify systematic extrapolation behavior in the following process (Subsection 4.3); (4) we document deviations from Bayesian learning among retail investors (Subsection 4.4)

4.1 The performance following relationship

Our baseline analysis investigates the determinants of follower acquisition, focusing particularly on past performance. We document a performance-following relationship wherein superior historical returns predict increases in new followers. Berk and Green (2004) demonstrate that retail investors use past returns to infer managerial skill, inducing performance chasing. Similarly, Han, Hirshleifer and Walden (2022) show that higher returns attract investor attention through representativeness heuristics. Consistent with these mechanisms, followers tend to extrapolate past performance as ability signals, generating social transmission bias.

We begin our analysis by estimating a regression model that links the number of new followers to investors' past performance, including both raw returns and alpha. Accordingly, we estimate the following two-way fixed effects panel regression:

$$Ln\,(1+New\,follower)_{i,t+1}=\alpha_j+\gamma_m+\beta_1 Performance_t+\lambda Ln\,(1+New\,follower)_{i,t}+\epsilon_{i,t}$$

The dependent variable is the logarithm of the number of new followers for user i in month $t + 1$. Our primary interest lies in the financial influencers' investment performance of mutual funds, measured by one-month return (*Ret_1M*) and three-month return (*Ret_3M*). α_j and γ_m represent investor fixed effect and the year-month fixed effect. Additionally, we include an AR(1) term to account for autocorrelation in new followers, while partially addressing the platform recommendation algorithm's influence and ensuring this technical adjustment does not artificially amplify the observed association between historical returns and subsequent follower acquisition.[18] Standard errors are clustered at the investor level in all models throughout the paper. Our analysis employs the complete sample of financial influencers, ensuring our focus on meaningful follower relationships. These active users substantially engage with the platform's social features, where new followers represent relevant attention.

Table 3 shows significantly positive coefficients for all performance measures (p<0.01), confirming the performance-following relationship. The results indicate economically significant effects: a 1% increase in *Ret_1M* and *Ret_3M* is associated with an increase in future new followers by 0.680% ($e^{0.00678} - 1$) and 0.242% ($e^{0.00242} - 1$), respectively, after controlling the investor fixed effect, time fixed effect and AR(1) term, with all coefficients being statistically significant at the 1% level.[19] Our findings align with Deng, Yang, Pelster and Tan (2023), Qi and Hull (2024) and Kakhbod, Kazempour, Livdan and Schuerhoff (2023), advancing the literature by employing panel data with new followers as the dependent variable reveals the dynamic influence accumulation process. Moreover, in Subsection 4.3, we will further show evidence that short-term raw returns (vs. risk-adjusted returns) and salient returns exhibit stronger predictive power for follower growth.

[18] The reported constant is the regression intercept after demeaning, and thus reflects the mean-adjusted level of the dependent variable.

[19] In all regressions, returns are scaled such that a one-unit increase corresponds to a 100 percentage point increase for a more precise showing. Accordingly, when the return increases 0.01 (1% point), it is associated with a 0.00678 increase in log (1+ new followers), which corresponds to an approximate 0.680% ($e^{0.00678} - 1$) multiplicative increase in new followers.

Table 3. Performance-following relationship between financial influencers and followers

Table 3 presents the regression results of the performance-following relationship between financial influencers and followers. Performance is measured by one-month return (*Ret_1M*) and three-month return (*Ret_3M*). T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	*Dependent Variable = Ln (1+New Follower)$_{t+1}$*					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ret_1M	0.820***		1.247***		0.678***	
	(12.487)		(11.418)		(7.695)	
Ret_3M		0.725***		0.974***		0.242***
		(12.869)		(9.455)		(4.182)
Ln (1+New follower)$_t$					0.638***	0.633***
					(118.795)	(114.568)
Constant	1.294***	1.299***	1.298***	1.305***	0.421***	0.427***
	(1893.495)	(844.800)	(1142.585)	(464.259)	(60.249)	(57.685)
Investor fixed effect	YES	YES	YES	YES	YES	YES
Year-Month fixed effect	NO	NO	YES	YES	YES	YES
R-squared	0.001	0.002	0.001	0.002	0.425	0.420
Observations	109197	98064	109197	98064	102793	96361

4.2 Robustness tests

4.2.1 Controlling for recommendation algorithm

On Ant Fund, the platform's recommendation algorithm functions as a pivotal factor influencing investment decision-making processes and modulating user engagement dynamics on social media platforms, potentially giving rise to alternative interpretations. To address potential effects from the platform's recommendation algorithm that exhibits inherent correlations with current returns and may independently affect follower growth patterns, we employ a comprehensive triple-dimensional control strategy incorporating algorithm-related variables across key operational aspects: (1) we control for investment activity measurement by utilizing total assets under management and the proportion of mutual fund investments relative to total assets (*Fund_pct, Ln(Asset)*) as proxy variables; (2) we control for content richness by applying the average length of user-generated opinions and financial influencers' reply activity levels (*Opinion_avg_len, Reply*); (3) we control for social engagement characteristics by using the total volume of opinions published, the number of fund-specific topics referenced within these opinions, and the range of topics subscribed to by financial influencers (*Ln(Opinion_all), Fund_ticker_num, Subscription_topic*).

As empirically demonstrated in Table 4, the *Ret_1M* coefficient maintains statistical significance at the 1% level across all model specifications, thereby robustly eliminating alternative explanatory pathways potentially driven by platform algorithm mechanisms.

Table 4. The results of excluding effects of recommendation algorithm

Table 4 presents the regression results that exclude the impact of platform recommendation algorithm by adding variables related to the recommendation algorithm step by step. T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	*Dependent Variable =*			
	Ln (1+New Follower)$_{t+1}$			
	(1)	(2)	(3)	(4)
Ret_1M	0.679***	1.534***	1.560***	1.554***
	(7.681)	(7.521)	(7.501)	(7.474)
Fund_pct	0.090***	0.141***	0.094**	0.096**
	(5.790)	(3.655)	(2.439)	(2.496)
Ln (Asset)	0.034***	0.058***	0.046***	0.046***
	(11.275)	(6.770)	(5.366)	(5.368)
Ln (1+New follower)$_t$	0.634***	0.603***	0.517***	0.514***
	(117.724)	(82.371)	(57.338)	(56.864)
Opinion_avg_len		0.000		-0.000
		(1.035)		(-0.332)

Variable Name	Dependent Variable =			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
Reply		0.000***		0.000***
		(6.624)		(4.127)
Ln (Opinion_all)			0.198***	0.189***
			(19.657)	(18.445)
Fund_ticker_num			-0.001	-0.001
			(-1.526)	(-1.486)
Subscription_ticker			-0.097	-0.102
			(-1.122)	(-1.180)
Constant	0.036	0.155	0.583	0.640
	(1.066)	(1.603)	(0.921)	(1.018)
Investor fixed effect	YES	YES	YES	YES
Year-Month fixed effect	YES	YES	YES	YES
R-squared	0.426	0.400	0.409	0.410
Observations	102498	40693	39832	39832

4.2.2 Other alternative specifications

Table 5 demonstrates the robustness of our core findings under a series of alternative model specifications. Across all panels, the coefficient on *Ret_1M*, the core variable used to test the extrapolation hypothesis, remains positive and statistically significant at the 1% level.[20] This consistency provides strong evidence that the observed performance-following relationship is not an artifact of specific model assumptions or sample definitions.

Panel A replaces the log-transformed dependent variable with the raw count of new followers, ensuring that our findings are not driven by functional form assumptions. Panel B introduces increasingly stringent sample restrictions, in which columns (1) and (2) limit the sample to financial influencers with at least one opinion post and a minimum asset level of 20,000 RMB per month, while columns (3) and (4) include only those with more than 500 followers, thus focusing on influential users with stable engagement.

In summary, our robustness checks reinforce the empirical credibility of our main result and support its interpretation as evidence of extrapolative bias, rather than platform-induced artifacts or sampling irregularities.

Table 5. Robustness Test

Table 5 shows the robustness of the performance-following relationship using different methods.

[20] We focus on the coefficient of *Ret_1M* as it is the most related variable to the extrapolation hypothesis, which will be discussed in the following section.

Panel A the result using *New follower* instead of *Ln (1+New follower)* as dependent variable. Panel B shows the result using a subsample of financial influencer having at least one opinion posting and 20,000 RMB asset each month (columns (1) and (2)), and financial influencer having at least 500 followers (columns (3) and (4)). T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Panel A. The robust results using *New follower* as dependent variable

Variable Name	***Dependent Variable =***	
	New follower$_{t+1}$	
	(1)	**(2)**
Ret_1M	65.657***	
	(4.244)	
Ret_3M		24.477**
		(2.358)
New follower$_t$	0.530***	0.529***
	(43.034)	(42.101)
Constant	31.113***	31.649***
	(33.559)	(31.930)
Investor fixed effect	YES	YES
Year-Month fixed effect	YES	YES
R-squared	0.287	0.283
Observations	102793	96361

Panel B. The robust results using subsample of financial influencer using different subsample

Variable Name	***Dependent Variable =***			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
Ret_1M	2.186***		0.779***	
	(8.822)		(5.135)	
Ret_3M		0.579***		0.115
		(3.430)		(1.209)
Ln (1+New follower)$_t$	0.623***	0.621***	0.582***	0.575***
	(78.392)	(76.325)	(73.339)	(70.150)
Constant	0.924***	0.933***	0.787***	0.797***
	(43.231)	(40.739)	(41.461)	(40.527)
Investor fixed effect	YES	YES	YES	YES
Year-Month fixed effect	YES	YES	YES	YES
R-squared	0.398	0.395	0.368	0.359
Observations	29812	28298	42274	39908

4.3 Overextrapolation in the performance following relationship

In both baseline results and robustness tests, *Ret_1M* (short-term investment performance) stands out as the strongest predictor of new followers in the subsequent month, a pattern consistent with extrapolation behavior. To evaluate whether retail investors' responses are driven by extrapolation in the social transmission bias, we delve deeper into two psychological features of investors: salience and heuristic reasoning. Behavioral theories posit that investors often recall salient past returns and use recent performance as a mental shortcut to infer ability. In Ant Fund, financial influencers can emphasize high-return assets in their portfolios, leading investors to overextrapolate from eye-catching but unrepresentative signals. Therefore, in this subsection, we empirically investigate three key aspects: (1) the contrast between visible versus skill-adjusted performance metrics, (2) the nonlinearity in performance-follower relationships, and (3) the interaction effects among salient returns.

4.3.1 Return presentation and positional visibility

Ant Fund's social media interface engineers a unique overextrapolation bias through customizable portfolio displays that allow influencers to sort holdings by size or performance (Figure 3), thereby accentuating extreme returns. This design amplifies the visibility of curated "star" performers, inducing systematic distortions in investors' performance evaluations.

Empirically, we compare the predictive power of two types of fund-level returns: the return of the single best-performing fund (*Ret_Max1*), and that of the most heavily held fund (*Ret_Core1*). While the former highlights salience, the latter reflects the importance of a fund in the portfolio. In Columns (1) and (2) of Table 6, the coefficients show that *Ret_Max1* has a significantly stronger effect on follower growth than *Ret_Core1*, with an estimated coefficient of 0.693 compared to 0.438, even though the latter represents a larger share of actual investment. This asymmetric response demonstrates how salient extremes distort attention, causing investors to overweight flashy outliers while neglecting the more representative (yet less eye-catching) core holdings that better reflect investment skills.

In Columns (3) and (4) of Table 6, we incorporate refined performance metrics, such as risk-adjusted alpha (*Alpha_3M*) and trade gains caused by timing ability (*Gain_Trade*), to evaluate financial influencers' skills. *Alpha_3M* measures fund alpha weighted by holding value, while Gain_*Trade* quantifies excess returns from strategic trades versus a buy-and-hold strategy. Despite better reflecting managerial skills, both metrics show weaker predictive power for follower growth than raw returns: the coefficient of *Alpha_3M* (declines to 0.216) and *Gain_Trade* (statistically insignificant at 0.103) demonstrates particularly limited explanatory power. This attenuation effect aligns with *Gain_Trade*'s absence from platform displays, confirming investors predominantly rely on visually accessible return metrics rather than obscured skill-based indicators.

These findings collectively demonstrate how performance presentation amplifies extrapolative biases. Investors systematically misattribute visible but noisy short-term outcomes to managerial skills, creating a persistent disconnect between perceived and actual investment ability. This misperception represents a key mechanism by which platform design distorts information aggregation, as salient yet economically insignificant signals dominate investor attention over meaningful skill indicators.

Table 6. Return presentation and performance following relationship

Table 6 examines how different return measures affect new follower growth. Column (1) includes the return of the best-performing fund in the portfolio (*Ret_Max1*). Column (2) replaces this with the return of the most heavily weighted fund (*Ret_Core1*). Column (3) includes *Alpha_3M*, which captures the risk-adjusted return of the portfolio. Column (4) includes *Gain_Trade*, which captures value added through investors' trading relative to a no-trading benchmark. T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	*Dependent Variable =*			
	Ln (1+New Follower)$_{t+1}$			
	(1)	(2)	(3)	(4)
Ret_Max1	0.693***			
	(9.641)			
Ret_Core1		0.438***		
		(6.433)		
Alpha_3M			0.216***	
			(3.140)	
Gain_Trade				0.103
				(0.454)
Ln (1+New follower)$_t$	0.637***	0.638***	0.638***	0.640***
	(118.618)	(118.745)	(118.914)	(118.9167)
Constant	0.379***	0.418***	0.416***	0.413***
	(48.612)	(60.110)	(59.937)	(59.257)
Investor fixed effect	YES	YES	YES	YES
Year-Month fixed effect	YES	YES	YES	YES
R-squared	0.425	0.424	0.425	0.426
Observations	102770	102539	102793	101724

4.3.2 Salient return and follower response sensitivity

Building on Da, Huang and Jin (2021)'s finding that return salience amplifies extrapolation, we demonstrate that the observed performance-following relationship reflects overextrapolation. First, we measure the salient of past returns by incorporating the quadratic term of investment performance into the regression equation to capture the nonlinear relationship between returns and number of new followers in the next month.

The regression model is:

$$Ln\ (1+New\ follower)_{i,t+1}=\alpha_j+\gamma_m+\beta_1 Performance_t+\beta_2 Performance_t^2+\lambda Ln\ (1+New\ follower)_{i,t}+\epsilon_{i,t}$$

Our quadratic specification aligns with Han, Hirshleifer and Walden (2022) theoretical framework, which models the information acquisition process as a quadratic function of investment strategy returns. Table 7 presents our empirical results using *Ret_1M* and *Ret_3M* as performance proxies. Most crucially, the significantly positive coefficient (1% level) for the quadratic term (*Ret_1M_sq*) indicates that higher returns generate disproportionately larger follower gains, consistent with extrapolation. This nonlinear effect appears unique to short-term raw returns (*Ret_1M*), as evidenced by the insignificant quadratic terms for *Ret_3M*, suggesting retail investors disproportionately focus on the most salient, recent performance metrics.

Table 7. The quadratic term of performance

Table 7 shows the results of adding quadratic term to the baseline model. Performance is measured by one-month return (*Ret_1M*) and three-month return (*Ret_3M*). T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name		***Dependent Variable =***	
		Ln (1+New Follower)$_{t+1}$	
	(1)	**(2)**	**(3)**
Ret_1M	0.727***		
	(8.026)		
Ret_1M_sq	3.285***		
	(3.202)		
Ret_3M		0.249***	
		(4.085)	
Ret_3M_sq		0.161	
		(0.461)	
Ln (1+New follower)$_t$	0.638***	0.633***	0.638***
	(118.825)	(114.589)	(118.876)
Constant	0.414***	0.426***	0.415***
	(55.908)	(55.017)	(59.002)
Investor fixed effect	YES	YES	YES
Year-Month fixed effect	YES	YES	YES
R-squared	0.425	0.420	0.425
Observations	102793	96361	102793

Second, as illustrated in Figure 3, financial influencers may display their investment portfolio sorted by return, making the highest-returning fund the most salient to investors. We measure salience by considering the highest return of the fund among the financial influencer's portfolio (*Ret_Max1*), we add a dummy variable for *Ret_Max1* (equals to 1 if higher than median) and its interaction term with *Ret_1M* into the regression, using the following model:

$$
\begin{aligned}
Ln\,(1+New\ follower)_{i,t+1} \\
&= \alpha_j + \gamma_m + \beta_1 Ret\_1M_{i,t} + \beta_2\, Ret\_max1\_Dummy_{i,t} \\
&+ \beta_3\, Ret\_max1\_Dummy_{i,t} * Ret\_1M_{i,t} + \beta x'_{i,t} + \epsilon_{i,t}
\end{aligned}
$$

Table 8 displays regression results with progressively added controls: Columns (1)-(2) include investor fixed effects, while Columns (3)-(4) incorporate both investor and time fixed effects, with Columns (2) and (4) additionally controlling for AR(1) terms. The consistently significant positive coefficient (1% level) for *Ret_Max1_dummy*Ret1M* across specifications indicates that salient returns amplify the performance-following relationship - direct evidence supporting extrapolative behavior.

To sum up, our results reveal a pronounced overextrapolation bias (Han, Hirshleifer and Walden (2022)): investors disproportionately reward extreme returns with their following behavior, treating standout performances as reliable skill indicators rather than potential outliers. This asymmetric response, where followers overweight salient wins far beyond rational benchmarks, demonstrates how vivid but statistically unreliable signals distort quality assessments on investment platforms.

Table 8. Salient return and performance-following relationship

Table 8 shows how salient return impact the performance-following relationship. We use max fund return in the holding portfolio (Re*t_Max1*) to proxy salient return and use its dummy of to construct an interaction term. T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	***Dependent Variable = Ln (1+New Follower)$_{t+1}$***			
	(1)	**(2)**	**(3)**	**(4)**
Ret_1M	0.284***	0.400***	0.418***	0.208**
	(3.203)	(5.390)	(3.166)	(1.981)
Ret_Max1_Dummy	0.125***	0.028***	0.131***	0.036***
	(10.692)	(3.381)	(10.521)	(4.137)

Variable Name	*Dependent Variable =*			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
Ret_Max1_Dummy*Ret_1M	0.709***	0.611***	0.653***	0.668***
	(4.858)	(5.198)	(4.328)	(5.521)
Ln (Asset)	0.107***	0.034***	0.104***	0.033***
	(16.807)	(11.842)	(15.762)	(10.966)
Fund_pct	0.277***	0.087***	0.265***	0.088***
	(10.227)	(5.766)	(9.553)	(5.651)
Ln (1+New follower)$_t$		0.638***		0.634***
		(124.070)		(117.631)
Constant	0.005	0.015	0.038	0.025
	(0.069)	(0.443)	(0.523)	(0.729)
Investor FE	YES	YES	YES	YES
Year-Month FE	NO	NO	YES	YES
R-squared	0.016	0.432	0.016	0.426
Observations	108882	102498	108882	102498

4.4 Rational learning in the social network as an alternative explanation

While our findings predominantly support overextrapolation, we formally assess competing explanations through a Bayesian learning. Under rational updating, follower responses should correlate with signal persistence and informativeness. We test this hypothesis by examining: (1) whether follower growth associates with persistent skill-driven returns, and (2) whether long-term performance aligns with Bayesian belief-updating patterns. These analyses disentangle sophisticated skill inference from behavioral biases in social investing contexts.

4.4.1 The precision of return as signal and performance-following relationship

Under rational Bayesian learning in social networks, investors' belief updating regarding financial influencers' skills — where stronger belief revision (and consequently amplified follower responses) increases with signal precision — aligns with theoretically predicted behavioral patterns. As emphasized in the mutual fund literature, the distribution of performance is informative for distinguishing skill from luck (Barras, Scaillet and Wermers (2010); Fama and French (2010)). Financial influencers with more stable performance — characterized by smaller month-to-month return differences, lower intra-month volatility, less variation across their fund holdings, or a higher proportion of positively performing funds — should exhibit a stronger relationship between current returns and new follower growth, as these attributes make returns more reflective of true investment ability.

Therefore, we conduct a heterogeneity analysis using four indicators: the difference between investment return in month *t* and month *t-1* (*Ret_dif*), the portfolio-weighted monthly return volatility in one month (*Vol_1m*), the variation of fund returns in investors' portfolio (*Ret_var*), and the proportion of funds with positive returns (*Posret*). For each indicator, we generate a dummy variable by comparing it to its median, the model is as follows:

$$
\begin{aligned}
&Ln\,(1+New\ follower)_{i,t+1} \\
&\qquad = \alpha_j + \gamma_m + \beta_1 Ret\_1M_{i,t} + \beta_2 Indicator\_Dummy_{i,t} \\
&\qquad + \beta_3 Indicator\_Dummy_{i,t} * Ret\_1M_{i,t} + \beta x'_{i,t} + \epsilon_{i,t}
\end{aligned}
$$

The results are reported in Table 9. In Panel A, the interaction term of *Ret_dif_dummy* and *Ret_1M* is insignificant. In Panel B, the interaction term of *Vol_1m_dummy* and *Ret_1M* is significantly positive at the 5% level. In Panel C, the interaction term of *Ret_var_dummy* and *Ret_1M* is significantly positive at the 1% level. In Panel D, the interaction term of *Posret*_dummy and *Ret_1M* is insignificant.

The performance-following relationship remains consistent across varying levels of monthly return differentials and proportions of positive-return funds, while paradoxically strengthening with higher intra-month portfolio volatility and greater cross-fund return variation - patterns incompatible with rational learning in the social network. While rational investors should discount volatile, isolated gains as luck, we nonetheless find the opposite: erratic, standout returns attract disproportionate attention. Paradoxically, performance noise amplifies, rather than reduces investors' tendency to chase top performers.

Table 9. The volatility of return and performance following relationship

Table 9 presents the regression results ruling out the alternative explanation of rational learning. Panel A to Panel D use the dummy variable of difference between investment return in month t and month t-1 (*Ret_dif*), the portfolio-weighted monthly return volatility in on month (*Vol_1m*), the variation of fund retur in investors' portfolio (*Ret_var*) the proportion of funds with positive returns (*Posret*) to construct an interaction term. T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Panel A. The results of the interaction term between *Ret1M* and *Ret_dif_dummy*

Variable Name	***Dependent Variable =***			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
Ret_1M	1.327***	0.844***	1.510***	0.680***
	(9.662)	(7.161)	(7.751)	(4.488)

Variable Name	*Dependent Variable =*			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
Ret_dif_dummy	-0.046***	-0.007	-0.044***	-0.003
	(-4.434)	(-0.958)	(-4.121)	(-0.362)
Ret_dif_dummy*Ret_1M	-0.635***	-0.098	-0.338*	0.000
	(-4.068)	(-0.717)	(-1.864)	(0.002)
Fund_pct	0.289***	0.089***	0.277***	0.090***
	(10.587)	(5.892)	(9.885)	(5.791)
Ln (Asset)	0.111***	0.035***	0.108***	0.034***
	(17.294)	(12.096)	(16.213)	(11.278)
Ln (1+New follower)$_t$		0.638***		0.634***
		(124.158)		(117.708)
Constant	0.051	0.027	0.089	0.038
	(0.730)	(0.810)	(1.242)	(1.099)
Investor fixed effect	YES	YES	YES	YES
Year-Month fixed effect	NO	YES	NO	YES
R-squared	0.014	0.432	0.014	0.426
Observations	108882	102498	108882	102498

Panel B. The results of the interaction term between *Ret1M* and *Vol1M_dummy*

Variable Name	*Dependent Variable =*			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
Ret_1M	0.627***	0.558***	1.015***	0.456***
	(5.509)	(5.897)	(6.335)	(3.566)
Vol1M_dummy	0.010	-0.002	0.011	0.004
	(0.559)	(-0.195)	(0.592)	(0.366)
Vol1M_dummy*Ret_1M	0.318***	0.285***	0.251*	0.274**
	(2.298)	(2.420)	(1.724)	(2.216)
Fund_pct	0.288***	0.090***	0.276***	0.091***
	(10.474)	(5.913)	(9.787)	(5.779)
Ln (Asset)	0.111***	0.035***	0.108***	0.034***
	(17.147)	(12.070)	(16.071)	(11.217)
Ln (1+New follower)$_t$		0.638***		0.634***
		(124.178)		(117.718)
Constant	0.025	0.023	0.064	0.034
	(0.364)	(0.695)	(0.888)	(1.006)
Investor fixed effect	YES	YES	YES	YES

Variable Name	Dependent Variable =			
	Ln (1+New Follower)$_{t+1}$			
	(1)	(2)	(3)	(4)
Year-Month fixed effect	NO	YES	NO	YES
R-squared	0.014	0.432	0.014	0.426
Observations	108882	102498	108882	102498

Panel C. The results of the interaction term between Ret1M and Ret_var_dummy

Variable Name	Dependent Variable =			
	Ln (1+New Follower)$_{t+1}$			
	(1)	(2)	(3)	(4)
Ret_1M	0.642***	0.509***	0.902***	0.364***
	(7.889)	(7.343)	(7.621)	(3.742)
Ret_var_dummy	0.076***	0.023***	0.081***	0.026***
	(6.703)	(3.013)	(6.930)	(3.344)
Ret_var_dummy*Ret_1M	0.443***	0.552***	0.566***	0.629***
	(2.975)	(4.575)	(3.696)	(5.089)
Fund_pct	0.284***	0.088***	0.272***	0.090***
	(10.424)	(5.840)	(9.743)	(5.750)
Ln (Asset)	0.109***	0.035***	0.106***	0.034***
	(17.007)	(11.930)	(15.945)	(11.111)
Ln (1+New follower)$_t$		0.638***		0.634***
		(124.036)		(117.579)
Constant	0.018	0.018	0.054	0.030
	(0.255)	(0.552)	(0.754)	(0.878)
Investor fixed effect	YES	YES	YES	YES
Year-Month fixed effect	NO	YES	NO	YES
R-squared	0.014	0.432	0.014	0.426
Observations	108882	102498	108882	102498

Panel D. The results of the interaction term between Ret1M and Posret_dummy

Variable Name	Dependent Variable =			
	Ln (1+New Follower)$_{t+1}$			
	(1)	(2)	(3)	(4)
Ret_1M	0.697***	0.663***	1.072***	0.584***
	(8.609)	(9.598)	(7.519)	(5.055)
Posret_dummy	0.052***	-0.001	0.042***	0.003
	(6.003)	(-0.187)	(3.984)	(0.427)
Posret_dummy*Ret_1M	0.293	0.323***	-0.166	0.208

Variable Name	Dependent Variable =			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
	(1.604)	(2.302)	(-0.785)	(1.272)
Fund_pct	0.284***	0.090***	0.273***	0.091***
	(10.411)	(5.917)	(9.768)	(5.802)
Ln (Asset)	0.110***	0.035***	0.108***	0.034***
	(17.185)	(12.155)	(16.116)	(11.293)
Ln (1+New follower)$_t$		0.638***		0.634***
		(124.194)		(117.727)
Constant	0.015	0.020	0.057	0.033
	(0.211)	(0.614)	(0.793)	(0.969)
Investor fixed effect	YES	YES	YES	YES
Year-Month fixed effect	NO	YES	NO	YES
R-squared	0.015	0.432	0.014	0.426
Observations	108882	102498	108882	102498

4.4.2 Short-term performance preference

In Table 3, return period decomposition (*Ret_1M* and *Ret_3M*) reveals investors' overwhelming focus on short-term performance, consistent with non-Bayesian learning models featuring imperfect recall (Molavi, Tahbaz Salehi and Jadbabaie (2018)). This contrasts sharply with rational learning predictions, where multi-period track records should dominate attention. Specifically, we should find that: (1) influencer returns should exhibit temporal persistence (predicting future performance), and (2) both current and past returns should significantly predict follower growth. These contrast sharply with the extrapolation hypothesis, where only the most recent and cognitively salient monthly return drives follower acquisition.

Panels A and B of Table 10 examine these two phenomena, respectively. In Panel A, historical returns negatively predict future returns, with the coefficients being both economically and statistically significant, which implies that the investment performance of financial influencers is not sustainable. In Panel B, we investigate whether a long-term stable performance-following relationship exists. The empirical findings indicate that only short-term investment returns (T and T-2) significantly contribute to an increase in the number of followers. In contrast, over the long term, superior investment performance does not appear to influence follower growth. Our results demonstrate a striking short-term bias: followers disproportionately chase recent high returns, regardless of volatility or luck, while largely ignoring long-term consistency, which reflects performance overextrapolation rather than rational social learning.

Table 10. The unsustainability of returns

Table 10 presents the results of the unsustainability of returns. In Panel A, we report the lasting impact of historical return on future performance. In Panel B, we show the lasting effect of the return on future new followers (*Ln (1+New Follower)*). T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Panel A. The forecasting of historical return on future return

Variable Name			*Dependent Variable =*		
			Ret_t+1		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Ret_T	-0.064***	-0.070***	-0.108***	-0.116***	-0.148***
	(-18.307)	(-18.162)	(-27.301)	(-25.446)	(-34.910)
Ret_T-1	-0.135***	-0.183***	-0.193***	-0.196***	-0.184***
	(-43.221)	(-57.735)	(-53.053)	(-47.230)	(-40.039)
Ret_T-2		-0.072***	-0.129***	-0.159***	-0.124***
		(-23.911)	(-36.820)	(-40.986)	(-28.953)
Ret_T-3			-0.154***	-0.165***	-0.190***
			(-44.358)	(-41.084)	(-46.408)
Ret_T-4				-0.092***	-0.061***
				(-24.434)	(-14.433)
Ret_T-5					-0.057***
					(-14.351)
Fund_pct	0.001**	0.002***	0.003***	0.003***	0.003***
	(2.151)	(3.800)	(4.952)	(4.843)	(4.526)
Ln (Asset)	-0.000	0.000	0.000***	0.000***	0.000**
	(-1.383)	(0.250)	(2.602)	(2.862)	(2.394)
Constant	-0.010***	-0.010***	-0.014***	-0.016***	-0.019***
	(-8.996)	(-9.030)	(-10.423)	(-11.513)	(-13.045)
Investor fixed effect	YES	YES	YES	YES	YES
Year-Month fixed effect	YES	YES	YES	YES	YES
R-squared	0.022	0.042	0.076	0.080	0.079
Observations	121572	114182	107048	100154	93528

Panel B. Unsustainability of performance-following relationship

Variable Name			*Dependent Variable =*		
			Ln (1+New Follower)$_{t+1}$		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Ret_T	0.671***	0.721***	0.803***	0.874***	0.819***
	(7.581)	(7.888)	(8.175)	(8.164)	(7.428)
Ret_T-1	-0.178**	-0.158*	-0.114	-0.111	0.005

Variable Name	*Dependent Variable =*				
	Ln (1+New Follower)$_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
	(-2.063)	(-1.762)	(-1.210)	(1.090)	(0.046)
Ret_T-2		0.207**	0.237**	0.233**	0.313***
		(2.307)	(2.480)	(2.327)	(2.837)
Ret_T-3			-0.025	0.013	0.037
			(-0.270)	(0.134)	(0.357)
Ret_T-4				0.085	0.156
				(0.889)	(1.520)
Ret_T-5					0.083
					(0.823)
Fund_pct	0.086***	0.091***	0.087***	0.083***	0.081***
	(5.434)	(5.528)	(4.974)	(4.539)	(4.238)
Ln (Asset)	0.035***	0.035***	0.034***	0.035***	0.033***
	(11.362)	(11.064)	(10.155)	(9.942)	(8.894)
Ln (1+New Follower)$_t$	0.636***	0.630***	0.626***	0.620***	0.612***
	(117.737)	(113.693)	(110.999)	(107.056)	(101.430)
Constant	0.027	0.026	0.047	0.059	0.087**
	(0.780)	(0.722)	(1.206)	(1.482)	(2.011)
Investor fixed effect	YES	YES	YES	YES	YES
Year-Month fixed effect	YES	YES	YES	YES	YES
R-squared	0.428	0.422	0.417	0.409	0.400
Observations	101448	96130	90821	85562	80478

To sum up, our findings do not support rational learning as the underlying mechanism of performance-following because investors do not respond to signal persistence or return stability, nor do they incorporate longer-term performance in a systematic way. Instead, they disproportionately follow influencers with volatile and dispersed returns. These patterns are inconsistent with Bayesian updating and suggest that social transmission in digital investment platforms is shaped less by informational quality than by distorted signals that circulate and reinforce influence in ways misaligned with investment fundamentals.

5. Amplification of overextrapolation bias

Building on our evidence that performance-following behavior reflects overextrapolation rather than rational learning in the social network, we now examine how financial influencers' social engagement patterns and portfolio characteristics may further amplify this bias in follower acquisition.

5.1 Following relationship based on other characteristics

Financial influencers' ability to attract followers depends critically on both their social interaction behavior (proxied by the log number of opinions posted, *Ln(Opinions)*) and investment style characteristics. Following Jones, Shi, Zhang and Zhang (2024), we measure investment style using: (1) total assets (*Ln(Asset)*), (2) mutual fund allocation ratio *(Fund_pct)*), and (3) index fund concentration (*Index_pct*)).[21] We estimate the following two-way fixed effects panel regression:

$$Ln\,(1+New\;follower)_{i,t+1}=\alpha_j+\gamma_m+\beta_1 Characteristics_t+$$

$$\lambda Ln\,(1+New\;follower)_{i,t}+\epsilon_{i,t}$$

Table 11 shows the results of social interaction and investment style. In Column (1), when the opinion posting increases by 1%, future new followers is increased by 0.171% ($e^{0.00171}-1$).[22] In Columns (2)-(4), one percent increase in *Fund_pct* is associated with an increase in future new followers by 0.072%, and one unit increase in *Index_pct* is associated with an increase in future new followers by 0.053%. When the total asset increases by 1%, future new followers is increased by 0.031%. All coefficients are statistically significant at the 1% level. Our findings suggest that the social interaction and investment style of financial influencers are also important reasons for attracting followers.

[21] Since prior research shows that the holdings of total assets may be a measure of investment ability (Jones, Shi, Zhang and Zhang (2024)).
[22] All remaining metrics in this paragraph follow analogous derivation.

Table 11. Following relationship based on other characteristics

Table 11 presents the regression results of the following relationship based on other characteristics of financial influencers. T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	*Dependent Variable =*			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
Ln (Opinion_all)	0.171***			
	(29.974)			
Fund_pct		0.072***		
		(4.706)		
Index_pct			0.053**	
			(2.204)	
Ln (Asset)				0.031***
				(11.092)
Ln (1+New follower)$_t$	0.532***	0.638***	0.641***	0.635***
	(83.026)	(118.710)	(119.100)	(118.178)
Constant	0.295***	0.365***	0.400***	0.119***
	(38.764)	(28.445)	(39.464)	(4.356)
Investor fixed effect	YES	YES	YES	YES
Year-Month fixed effect	YES	YES	YES	YES
R-squared	0.439	0.425	0.427	0.426
Observations	102498	101044	102793	102793

5.2 The role of delegation

The strength of the performance-following relationship is moderated by return attribution patterns. We posit that that index-fund-dominated portfolios reduce perceived delegation, leading investors to directly attribute returns to the influencer's skill more. This attribution mechanism consequently amplifies both the performance-following relationship and overextrapolation bias.[23]

To test this hypothesis, we include an interaction term between index fund holdings and investment returns in the regression model.[24]

[23] Prior studies suggest that the delegation of decision-making often leads investors to shift responsibility of investment failure to fund managers rather than themselves (Bartling and Fischbacher (2012); Chang, Solomon and Westerfield (2016); Freer, Friedman and Weidenholzer (2023)). Moreover, Chang, Solomon and Westerfield (2016) find that index funds play a less important role in delegated management than actively managed funds.

[24] It should be noted that there is no empirical evidence to show that there are significant differences in financial literacy between investors who choose active funds and those who choose passive funds in the Chinese mutual fund market.

$$Ln\,(1 + New\,follower)_{i,t+1}$$
$$= \alpha_j + \gamma_m + \beta_1 Ret\_1M_{i,t} + \beta_2 Index\_Dummy_{i,t}$$
$$+ \beta_3 Index\_Dummy_{i,t} * Ret\_1M_{i,t} + \beta x'_{i,t} + \epsilon_{i,t}$$

The investment returns are measured by Ret_1M, and $Index\_Dummy$ is a variable that equals to 1 if $Index\_pct$ at month t is higher than the median and 0 otherwise. $Index\_Dummy_{i,t} * Ret\_1M$ is the interaction term. $x'_{i,t}$ is a vector of control variable associated with individual investor i in month t, including $Fund\_pct$ and *Ln (Asset)*. α_j and γ_m represent investor fixed effect and the year-month fixed effect.

The results of the regression are reported in Table 12. We find that the coefficients in Columns (1) and (4) do not change that much, meaning that adding the two-way fixed effect and AR(1) term does not affect the relationship of investment return and future new followers. In Column (4), the coefficient on $Index\_Dummy_{i,t} * Return$ is 0.371, which is significant at the 1% level. Therefore, when the index holdings of influencers on the platform are below the median, one percent increase in one month's return is associated with an increase of 0.484% ($e^{0.00483} - 1$) in future new followers. When the index holdings are above the median, an increase of 0.858% ($e^{0.00854} - 1$) is observed.[25]

These results indicate that for influencers who heavily invest in index funds, the performance-following relationship is stronger. This finding highlights how index fund investment influences the process by which investors gain social influence and become financial influencers. It also helps explain the earlier results in Table 2, in which financial influencers on social media platforms invest heavily in index funds as their level of influence increases: by investing heavily in index funds, financial influencers may be strategically positioning themselves to ensure that their investment success is attributed to their own skill rather than to mutual fund managers, thereby strengthening their appeal to

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[25] The result of index holdings above median reported in the paragraph is the sum of the coefficient of *Return* and *Index_Dummy * Ret_1M* (e.g., 0.854=0.483+0.371 in Column (4) of Table 12).

potential followers.

Table 12. Delegation and extrapolation

Table 12 presents regression results on how the performance-following relationship varies with the delegation level of investment, which is proxied by index fund holding (*Index_dummy*). T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	*Dependent Variable =*			
	Ln (1+New Follower)$_{t+1}$			
	(1)	(2)	(3)	(4)
Ret_1M	0.636***	0.567***	1.010***	0.483***
	(6.720)	(6.818)	(7.918)	(4.507)
Index_Dummy	0.081***	0.030**	0.087***	0.037***
	(2.994)	(2.157)	(3.178)	(2.584)
*Index_Dummy*Ret_1M*	0.408***	0.356***	0.408***	0.371***
	(3.197)	(3.146)	(3.090)	(3.178)
Ln (Asset)	0.109***	0.034***	0.106***	0.033***
	(16.858)	(11.724)	(15.763)	(10.860)
Fund_pct	0.280***	0.086***	0.267***	0.087***
	(10.135)	(5.655)	(9.430)	(5.506)
Ln (1+New follower)$_t$		0.638***		0.634***
		(124.201)		(117.721)
Constant	0.015	0.017	0.053	0.029
	(0.211)	(0.526)	(0.734)	(0.863)
Investor FE	YES	YES	YES	YES
Year-Month FE	NO	NO	YES	YES
R-squared	0.015	0.432	0.014	0.426
Observations	108882	102498	108882	102498

5.3 Social interaction and overextrapolation

In this subsection, we test whether the influencers' social interaction behavior on the platform amplifies overextrapolation bias and causes a stronger performance-following relationship. Hong, Lu and Pan (2019) suggests that the concentration of information flow and product distribution on Fintech platform amplify the sensitivity of fund flows and past performance. Similarly, due to the impact of information dissemination on influencers behaviors, social interaction on the platform may also increase the performance-following relationship. To test this hypothesis, we add interaction term of opinion posting behavior and investment returns into the model:

$$Ln\,(1+New\ follower)_{i,t+1}$$
$$= \alpha_j + \gamma_m + \beta_1 Ret\_1M_{i,t} + \beta_2 Posting\_Dummy_{i,t}$$
$$+\ \beta_3 Posting\_Dummy_{i,t} * Ret\_1M_{i,t} + \beta x'_{i,t} + \epsilon_{i,t}$$

We consider the interaction term by using $Posting\_Dummy$, a dummy variable of opinion posting (if number of the opinion posting is above the median, $Posting\_Dummy$ =1, otherwise $Posting\_Dummy$ =0). The investment returns are measured by *Ret_1M*, the monthly investment return of mutual fund; $x'_{i,t}$ is a vector of control variables associated with individual investor i in month t, including $Fund\_pct$ and *Ln (Asset)*. α_j and γ_m represent investor fixed effect and the year-month fixed effect.

We show the stepwise adding of AR(1) terms and fixed effect in Table 13. With two-way effect and AR(1) term (Column (4)), the coefficient on $Posting\_Dummy_{i,t} * Return\_1M$ is 1.325 and is significant at the 1% level. In summary, for influencers who post opinions more than median level, one percent increase in the monthly returns is associated with a 1.491% ($e^{0.01480} - 1$) increase in future new followers. For influencers who post opinions less than median level, the effect is only 0.155% ($e^{0.00155} - 1$).

Table 13. Social interaction and extrapolation

Table 13 presents regression results on how the performance-following relationship varies with social interaction behavior, which is proxied by the posting behavior (*Posting_dummy*). T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	***Dependent Variable =***			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
Ret_1M	0.173***	0.241***	0.278***	0.155*
	(3.459)	(4.971)	(3.058)	(1.930)
Post_Dummy	1.120***	0.186***	1.112***	0.197***

Variable Name	***Dependent Variable =***			
	Ln (1+New Follower)$_{t+1}$			
	(1)	**(2)**	**(3)**	**(4)**
	(46.087)	(14.390)	(43.600)	(14.770)
Post_Dummy*Ret_1M	1.957***	1.354***	1.896***	1.325***
	(12.990)	(10.222)	(12.374)	(9.793)
Ln (Asset)	0.076***	0.032***	0.077***	0.031***
	(13.610)	(11.042)	(13.263)	(10.347)
Fund_pct	0.202***	0.081***	0.196***	0.083***
	(8.254)	(5.392)	(7.879)	(5.352)
Ln (1+New follower)$_t$		0.622***		0.617***
		(114.553)		(109.925)
Constant	-0.038	0.009	-0.032	0.017
	(-0.605)	(0.276)	(-0.500)	(0.513)
Investor FE	YES	YES	YES	YES
Year-Month FE	NO	NO	YES	YES
R-squared	0.095	0.435	0.095	0.429
Observations	108882	102498	108882	102498

We next examine the amplification mechanism, focusing on selective disclosure as a potential channel. Building on Han, Hirshleifer and Walden (2022) finding of self-enhancement reporting in information transmission, we test whether financial influencers exhibit higher posting frequency following strong performance periods. Such strategic disclosure could systematically distort followers' ability assessments and exacerbate overextrapolation.

We first test whether posting behavior is affected by their recent investment performance by estimating the following model:

$$
\begin{aligned}
Ln(1+Opinion)_{i,t+1} \\
&= \alpha_j + \gamma_m + \beta_1 Performance_{i,t} + \lambda Ln(1+Opinion)_{i,t} \\
&+ \beta x'_{i,t} + \epsilon_{i,t}
\end{aligned}
$$

The dependent variable, $Ln(1+Opinion)_{i,t+1}$, is the logarithm of the number of postings of opinions of each user i on month $t+1$. The independent variable *Return* is measured by *Ret_1M*, *Ret_3M*, *Alpha_3M*. $x_{i,t}^{'}$ represents the control variable associated with individual investor i in month t, which is $Fund\_pct$ and *Ln (Asset)* and the AR(1) term of the dependent variable. α_j and γ_m represent investor fixed effect and the year-month fixed effect.

The results are reported in Table 14. One percent increase in *Ret_1M*, *Ret_3M*, *Alpha_3M* is associated with a 0.651% ($e^{0.00649} - 1$), 0.191%, and 0.300% increase in future number of opinion posting, all coefficients are significant at the 1% level. Our findings align with both theoretical predictions from Han, Hirshleifer and Walden (2022) and empirical evidence in Sui and Wang (2022), demonstrating that posting frequency increases with investment returns. This selective disclosure behavior distorts followers' information sets, creating a self-reinforcing cycle that amplifies performance-chasing behavior.

Table 14. The results of self-enhancement report

Table 14 presents regression results on the relationship between posting and past investment performance. T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name		***Dependent Variable =***	
		Ln (1+Opinion)$_{t+1}$	
	(1)	**(2)**	**(3)**
Ret_1M	0.649***		
	(8.401)		
Ret_3M		0.191***	
		(3.690)	
Alpha_3M			0.300***
			(4.843)
Ln (Asset)	0.050***	0.050***	0.050***
	(18.663)	(16.863)	(18.683)
Fund_pct	0.166***	0.173***	0.166***
	(11.794)	(11.290)	(11.783)
Ln (1+Opinion)$_t$	0.662***	0.658***	0.662***
	(142.837)	(133.693)	(142.928)
Constant	-0.134***	-0.138***	-0.139***
	(-4.587)	(-4.201)	(-4.776)
Investor FE	YES	YES	YES
Year-Month FE	YES	YES	YES

Variable Name	**Dependent Variable =**		
	Ln (1+Opinion)$_{t+1}$		
	(1)	**(2)**	**(3)**
R-squared	0.461	0.453	0.461
Observations	130790	115391	130790

We further test whether self-enhancing reporting responds only to recent performance by sequentially incorporating lagged monthly returns (T-1 to T-5) as predictors. Table 15 reveals that only T-2 returns significantly predict posting activity, confirming this disclosure bias exhibits pronounced recency effects, responding primarily to contemporaneous returns while largely ignoring historical performance.

Table 15. Unsustainability of self-enhancing reporting

Table 15 presents regression results on how the relationship between posting and past investment performance from T to T-5. T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	***Dependent Variable =***				
	Ln (1+Opinion)				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Ret_T	0.690***	0.703***	0.785***	0.842***	0.738***
	(8.581)	(8.472)	(8.816)	(8.531)	(7.180)
Ret_T-1	-0.216***	-0.182**	-0.156*	-0.150	-0.011
	(-2.763)	(-2.251)	(-1.836)	(-1.624)	(-0.109)
Ret_T-2		0.091	0.198**	0.169**	0.243***
		(1.172)	(2.429)	(1.968)	(2.582)
Ret_T-3			0.195**	0.213**	0.150
			(2.419)	(2.437)	(1.595)
Ret_T-4				-0.074	0.026
				(-0.876)	(0.284)
Ret_T-5					0.013
					(0.141)
Fund_pct	0.172***	0.173***	0.170***	0.169***	0.164***
	(11.822)	(11.269)	(10.618)	(9.992)	(9.247)
Ln (Asset)	0.050***	0.050***	0.048***	0.047***	0.046***
	(17.795)	(16.853)	(15.431)	(14.325)	(13.258)
Ln (1+Opinion)	0.663***	0.658***	0.654***	0.646***	0.638***
	(138.950)	(133.751)	(128.631)	(121.552)	(114.838)
Constant	-0.141***	-0.137***	-0.106***	-0.086**	-0.063
	(-4.561)	(-4.175)	(-3.059)	(-2.306)	(-1.591)

Variable Name	*Dependent Variable =*				
	Ln (1+Opinion)				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Investor FE	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES
R-squared	0.459	0.454	0.446	0.434	0.424
Observations	122952	115391	108093	101051	94344

To sum up, our findings suggest that social interaction contributes to the amplification of extrapolative bias in digital investment platforms. Higher posting frequency magnifies the sensitivity of follower acquisition to recent returns, while posting behavior itself responds selectively to favorable performance. This pattern reflects a self-reinforcing disclosure dynamic, wherein upward-biased information supply exacerbates return-based social transmission. The interplay between return-driven communication and follower response generates a distortion in how investment ability is perceived and diffused, reinforcing patterns of influence formation that are decoupled from fundamental skill and shaped by strategically curated signals.

6. Real impact on retail investors

Financial influencers' social interactions significantly shape retail investors' decisions through dual channels: direct strategy imitation by trusting followers and algorithmic amplification of influencer content. As posting frequency increases, platform algorithms preferentially distribute influencer content, focusing investor attention on recommended funds and biasing trading decisions. We quantify this transmission mechanism using the monthly new follow behavior to other users (*Follow_op*) as the proxy of investor new following behavior to financial influencers, empirically testing the cascading impact of financial influencers on retail investment actions.[26]

6.1 Impact of financial influencers on followers' investment return

Investment performance is the primary concern for investors and deeply reflects the welfare impact that financial influencers on fintech platforms bring to ordinary investors. To examine the real effect, we first examine the effect of *Follow_op* on investors' returns in the following month, and the regression model is as follows:

$$Ret_{i,t+1} = \alpha_j + \gamma_m + \beta_1 Follow\_op_{i,t} + \beta x'_{i,t} + \epsilon_{i,t}$$

In order to alleviate the concern that the total return of the portfolio in the next month may be affected by the investment decisions made before retail investors following a

[26] Since we cannot obtain the list of followers of financial influencers, we can only observe the number of their followers. We use the data of investors' subscription on verified-influencer here and treat it as the investors' subscription on financial influencers.

financial influencer, we further compute the profit (loss) from trading in the next month (*Gain_Trade*). To calculate *Gain_Trade* for each investor in each month, we first estimate the counterfactual return which assumes that the investor maintains the same portfolio from the end of the previous month without any changes. We then compare the actual return with the counterfactual return to determine the profit (loss) from trading. Finally, we examine the effect of *Follow_op* on investors' profit (loss) from trading in the following month, the regression model is as follows:

$$Gain\_Trade_{i,t+1} = \alpha_j + \gamma_m + \beta_1 Follow\_op_{i,t} + \beta x_{i,t}^{'} + \epsilon_{i,t}$$

Columns (1) and (2) of Table 16 present the regression results of *Ret (bp)* and *Gain_Trade (bp)*, respectively. We find the coefficients of *Follow_op* are -0.568 and -0.835, and both are statically significant at the 1% level. Overall, *Follow_op* has a negative impact on both next-month returns and trade-related profits. This further indicates that the following behavior of investors towards financial influencers may be ineffective.

6.2 Impact of financial influencers on followers' index fund allocation

In Section 5, we find that the holdings of index funds amplify the performance-following relationship. Therefore, we believe that the good performance of index funds held by financial influencers is more likely to affect individual investors, so investors who follow financial influencers will increase their holdings in index funds. We then examine the effect of *Follow_op* on change of index fund holding in the following month (*Index_chg* (%)), the regression model is as follows:

$$Index\_chg_{i,t+1} = \alpha_j + \gamma_m + \beta_1 Follow\_op_{i,t} + \beta x_{i,t}^{'} + \epsilon_{i,t}$$

Column (3) of Table 16 reports the regression result of *Index_chg* (%), the coefficient of *Follow_op* is 0.033 and statically significant at the 1% level. Our finding suggests that the following behavior of investors towards financial influencers may lead to the portfolio adjustment and change the preference of fund type.

6.3 Impact of financial influencers on followers' return volatility

Han, Hirshleifer and Walden (2022) suggests that social transmission bias tends to amplify the spread of more volatile strategies on the social environment. We empirically examine this hypothesis by examining the economic effect of *Follow_op* on the average volatility of investors' fund holdings (*Vol_1m*). The calculation method of *Vol_1m* is provided in the Appendix. When investors allocate a larger portion of their portfolio to high-volatility funds, *Vol_1m* increases, which is estimated in the following regression:

$$Vol\_1M_{i,t+1} = \alpha_j + \gamma_m + \beta_1 Follow\_op_{i,t} + \beta x'_{i,t} + \epsilon_{i,t}$$

Column (4) of Table 16 reports the regression results of *Vol_1m*, the significant and positive coefficient of *Follow_op* is consistent with our hypothesis, indicating that the tendency of retail investors to follow financial influencers can enhance their preference toward high-risk funds. In some sense, if retail investors lack the capacity to withstand the risks associated with such investment products, the irrational following behavior may not only increase risk exposure but also intensify risk misallocation, ultimately impacting their investment returns.

Table 16. The impact of following behavior on the investment strategy of retail investors

Table 16 reports regression results on the impact of following financial influencer to the return (*Ret, Gain_Trade*) and investment strategy like preference for index fund (*Index_pct_chg*) and high volatility strategy (*Vol_1m*) of retail investor. *Ret*, *Gain_Trade* and *Vol_1m_chg* is calculated using basis point, *Index_pct_chg* is calculated using percentage. T-Statistics in parenthesis, ***, ** and * represent significance at the 1%, 5% and 10% respectively.

Variable Name	*Dependent Variable =*			
	Ret	**Gain_Trade**	**Index_chg**	**Vol_1m**
	(bp)	**(bp)**	**(%)**	**(bp)**
	(1)	**(2)**	**(3)**	**(4)**
Follow_op	-0.568***	-0.835***	0.033***	0.280***
	(-3.265)	(-7.517)	(3.396)	(12.410)
Ret_1M_t	-0.040***	0.018***		
	(-32.411)	(18.936)		
$Index\_pct_t$			-0.360***	
			(-138.188)	
Vol_1m_t				-0.496***
				(-178.221)
Ln (Asset)	-11.812***	-2.544***	0.169***	0.340***
	(-14.334)	(-4.454)	(3.086)	(2.637)
Fund_pct	28.535***	8.618***	-0.942***	-1.699***
	(11.771)	(4.633)	(-5.974)	(-4.792)
Constant	13.638	13.412**	11.735***	58.510***
	(1.388)	(1.963)	(17.740)	(35.900)
Investor FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
R-squared	0.002	0.002	0.180	0.252

Variable Name	*Dependent Variable =*			
	Ret (bp)	**Gain_Trade (bp)**	**Index_chg (%)**	**Vol_1m (bp)**
	(1)	**(2)**	**(3)**	**(4)**
Observations	685158	685158	682370	685158

7. Conclusion

Financial influencers have become pivotal actors in the digital financial information ecosystem, yet the mechanisms through which they shape retail investor behavior remain poorly understood. Using unique data from Ant Fund, we find that the influence of financial influencers stems largely from behavioral biases. We show that retail investors' tendency to follow influencers with strong past performance reflects overextrapolation rather than rational learning in the social network, particularly more pronounced for extreme short-term returns that is proved unsustainable. This performance-following dynamic is further amplified when influencers hold more index funds or actively engage in social posting — patterns consistent with self-enhancing reporting biases. Critically, our results demonstrate that following financial influencers leads to worse investment outcomes, as it encourages excessive allocations to index funds and high-volatility assets while depressing overall returns.

Our study yields two key insights for social finance platforms: First, we identify a fundamental disconnect between perceived and actual investment competence, driven by investors' tendency to overweight salient but uninformative signals. Second, we demonstrate how platform architectures that prioritize eye-catching displays over substantive financial metrics systematically amplify these behavioral distortions. These findings highlight the pressing need for platform design reforms and investor safeguards.

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Appendix A. Variable Definitions

1. Individual level variables

Age: The age of the investor (financial influencer).

App_use: The year since the investor registered App.

Gender: A female dummy variable, Gender =1 if investor is female otherwise Gender =0.

Risk-tolerance: The investor's risk-tolerance level evaluated by the App ranking from 1 to 5, wherein a scale of 1-5 corresponds to varying levels of risk tolerance: low, moderately low, moderate, moderately high, and high respectively.

2. Individual-month level variables

Asset: The total value of assets an investor holds on the platform at the end of the month.

Follow_op: The number of financial influencers an investor follows during the month.

Fund_pct: The proportion of fund investment to total asset, calculated as $\frac{Total\,Fund\,Assets}{Total\,Assets}$

Fund_ticker_num: the number of fund-related topics included in opinions.

Index Fund Assets: The total value of index fund holdings an investor owns at the end of the month. The classification of a fund is based on its label on the AntFund Platform.

Index_pct: The proportion of index fund, calculated as $\frac{Index\,Fund\,Assets}{Total\,Fund\,Assets}$.

New follower: The net increase in the number of users following an investor at the end of the month compared to the beginning of the month.

Like_op: The number of posts a Retail investor chooses to "like" during the month.

Opinion_avg_len: The average number of characters of opinions.

Opinions: The total number of posts an investor publishes on the platform during the month.

Read_op: The total time an investor spends reading posts on the platform during the month, measured in minutes.

Reply: The number of the financial influencer's reply to the retail investor.

Ret_1M: The monthly investment Return, calculated as:

$$\frac{Investment\ Profit}{Average\ fund\ assets}$$

$Investment\ Profit$ is total profit or loss an investor has on mutual fund investments, which is provided by the platform, as the aggregation of paper gains (losses) and realized gains (losses).

Ret_3M: The cumulative sum of Ret_1M over the past three months.

Subscription_topic: the number of topics subscribed by financial influencers.

Total Followers: The number of users following an investor at the end of the month.

Total Fund Assets: The total value of mutual fund an investor had at the end of the month.

3. Individual-month level variables derived from detail information of fund-holding

Using the information of investor *i*'s holding amount in each fund *f* in month *t* ($Fund\_asset_{i,f,t}$), we can derive variables as followed:

Alpha_3M: The weighted average of $fund\_alpha3m$ for the funds held by the investor, with weights assigned based on the investor's holding amount in each fund, calculated as:

$$Alpha\_3M_{i,t} = \sum_{f\in F_{i,t}} \left(\frac{fund\_asset_{i,f,t}}{\sum_{f\in F_{i,t}} fund\_asset_{i,f,t}} \cdot fund\_alpha3m_{f,t}\right)$$

For every fund *f* and every month *t*, $fund\_alpha3m$ are obtained from the WIND database, calculated based on the daily Return of fund and the benchmark Return according to the fund prospectus in the past three months:

$$fund\_ret_{f,d} = fund\_alpha3m_{f,t} + \beta_{f,t} * benchmark_{f,d} + \epsilon_{d,t}$$

Gain_Trade: The difference between *Ret_1M* and the counterfactual return ($CFRET$) (an investor would have earned if they made no trades during the month). The counterfactual Return is calculated based on the detail fund holding information, for each fund *f* in the investors' investment portfolio *F*, we sum the monthly Return of each fund ($fund\_ret_{f,t}$), with weights assigned based $fund\_asset_{i,f,t}$:

$$CFRET_{i,t} = \sum_{f\in F_{i,t}} \left(\frac{fund\_asset_{i,f,t}}{\sum_{f\in F_{i,t}} fund\_asset_{i,f,t}} \cdot fund\_ret_{f,t}\right)$$

Posret: The proportion of fund with positive return in all the fund the investor holds, calculated as $\frac{\sum_{f\in F_{i,t}} 1(Fund\_ret_{f,t}>0)}{|F_{i,t}|}$, $F_{i,t}$ denotes the set of funds held by investor i in month t. $|F_{i,t}|$ is the cardinality of $F_{i,t}$, meaning the number of funds the investor holds in that month. $Fund\_ret_{f,t}$ represents the return of fund f in month t. $1(Fund\_ret_{f,t} > 0)$ is an indicator function.

Ret_Core1: The one-month return of the fund in the investor's portfolio which is held most heavily:

$$Ret\_Core1_{i,t} = Fund\_ret_{k^*,t},\ where\ k^* = \arg\max_{f\in F_{i,t}} (Fund\_asset_{f,t})$$

Ret_Max1: The highest one-month return of the fund in the investor's portfolio:

$$Ret\_Max1_{i,t} = \max_{f\in F_{i,t}} (Fund\_ret_{f,t})$$

Ret_var: The standard deviation of fund returns within investor *i*'s portfolio $F_{i,t}$, calculated as $StdDev(Fund\_ret_{f,t} / f \in F_{i,t})$

Vol_1M: The weighted average of $fund\_vol$ for the funds held by the investor, with weights assigned based on the investor's holding amount in each fund, calculated as:

$$Vol\_1M_{i,t} = \sum_{f\in F_{i,t}} (\frac{fund\_asset_{i,f,t}}{\sum_{f\in F_{i,t}} fund\_asset_{i,f,t}} \cdot fund\_vol_{f,t}$$

For every fund *f* and every month *t*, $fund\_vol$ are obtained from the WIND database, computed as the standard deviation of the fund's daily Returns over the month.