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By **Shixiang Cao, Zhigang Qiu, Luyao Shen, Ke Song, Taining Yan** *

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Abstract

Using unique data from Ant Group, we examine how social interactions influence trading behaviour and whether posting enhances investment returns. We show that posting significantly boosts fund trading, including subscriptions and redemptions. We also demonstrate that posting-driven trading facilitates social learning for investors. First, posting positively impacts investment returns. Second, while trading initially negatively affects returns, the impact is temporary and diminishes over time, suggesting that short-term losses reflect learning costs. Finally, the negative effect of posting-driven trading on returns is short-lived, with long-term returns improving as investors incorporate effective price signals gained through social learning.

JEL Classification: D14, G11, G41
Keywords: fintech, individual mutual fund investors, online posts, social learning, trading behaviour

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1. Introduction

One of the most prominent features of the Internet era is the big data generated by Internet users, and the information contained in the big data is usually considered to provide added value to the financial and real sectors, supporting the development of the so-called 'web 2.0' (e.g., Goldstein et al. 2021; Einav and Levin 2014).[1] In various forms of big data, we often see posts expressing opinions or sharing experiences on various social media platforms, especially in the finance industry. Due to the high dependence of practitioners in the finance industry on information, posts on financial social media are often considered to have a significant impact on the investors' financial decision-making (e.g., Han and Yang 2013; Ammann and Schaub 2021). For example, Chen et al. (2014) document that opinions posted by investors from Seeking Alpha, one of the most popular financial social media in the United States, can predict future stock returns and earnings surprises. While the peer posts seem to contain useful information, it is well known that those data (posts) are full of noises (e.g., Kim and Kim 2014). Therefore, although extensive research has been conducted on the value of information in social media in the literature, the co-existence of information and noise in posts results in mixed empirical results at best (e.g., Tumarkin and Whitelaw 2001; Bartov et al. 2023; Crawford et al. 2017). In this paper, we apply the unique data of Ant Fund, the fund trading platform of Ant Group, to examine how individual investors learn from various posts in the context of Chinese mutual fund investors.

Ant Fund is one of the largest wealth management platforms in China, operated by Ant Group. At present, there are over 150 asset management institutions on the Ant Fund platform that provide various fund products to hundreds of millions of investors, including money market funds (Yu E Bao), index funds, and bond funds et al. The Ant Fund platform not only provides the largest fund sales service in China for individual fund investors but also provides a highly active interactive community where investors can share various information contents through posts. Through the Ant Fund platform, we can obtain data on investor characteristics, online interactions of various posts, fund trading activities, and investment returns, providing an ideal environment for our research.[2]

The information in investor posts is usually a combination of information and noise. First, posting on social platforms encourages more investors to participate in discussions and responses, allowing them to receive valuable feedback (e.g., Crawford et al. 2017; Bursztyn et al. 2014; Stein 2008). Therefore, posting could provide valuable information, as engaging in social learning enables investors to acquire more private information through communication with others (e.g., Bala and Goyal 1998; Bloche 2016). Second, investors may post to achieve self-fulfillment because posters want to attract followers and hope to become opinion leaders by sharing attractive posts, showcasing their investment ability in expanding influence (e.g., Cao et al. 2024). Third, investors may post to express and incite emotions, especially when their investment performance is poor. There are often many posts expressing anxiety or frustration about mutual fund managers when the overall market declines. These posts are usually characterised by sharp language, containing a lot of personal emotions and noise (e.g., Pedersen 2022).

The impact of social interaction on investor behaviour could potentially be contrary to expectations, the superficially contradictory phenomena is driven by two channels, namely the information channel and the amplification channel, respectively. On the one hand, information channel refers that investors can learn from social interaction by evaluating,

summarizing, and reading replies by posts. In particular, investors actively participate in online interactions by posting (especially by asking questions), obtaining valuable price signals from replies and responses from other investors, and continuously updating their information set (e.g., Chen et al. 2014; Crawford et al. 2017). On the other hand, amplification channel refers to the irrational behaviour of investors being amplified by noisy posts that purely express emotions (e.g., Heimer and Simsek 2019).[3] It is very common for investors to spread false information and vent their emotions through posts, and this kind of posting gains the affirmation of followers, thereby strengthening the misunderstandings of the posters.

We begin our analysis by examining the causal relationship between posting behaviour and investors' fund trading activity. Specifically, we perform regression analysis, controlling for return, fund holdings, investor fixed effects, and year-month fixed effects. Our empirical results show that posting significantly increases investors' fund trading activity. Specifically, a 1% increase in investor posts leads to a significant 0.035% (0.059%) increase in total trading frequency (amount) in the following month. We also separately estimate the relationship between fund subscriptions and redemptions and investors' postings, finding that posting increases both the frequency and volume of transactions for both subscriptions and redemptions. Moreover, the positive impact of posting on trading persists for up to 6 months.

To ensure the robustness of our baseline results, we perform several additional tests. First, we restrict the sample to investors who have posted, excluding those with no social interaction. Second, we replace the continuous posting measure with a binary indicator to test threshold effects. Third, we substitute the dependent variable with turnover, capturing portfolio adjustment intensity.[4] Across all specifications, the relationship between posting and trading remains statistically significant, confirming that the effect is not sensitive to model specification, sample composition, or confounding platform activities.

To tackle potential endogeneity concerns arising from unobservable individual characteristics or reverse causality, we employ two strategies. First, we employ IV (instrumental variable) estimation using peer-based posting measures as instruments (Hong et al. 2005; De Giorgi et al. 2010; De Giorgi and Pellizzari 2014). These measures include group-level averages from investors with similar demographic traits (Same Personality), geographic location (Same City), and both (Same Personality and City). The instruments variables are strongly correlated with individual posting but exogenous to trading behaviour. Second, we apply propensity score matching (PSM) based on key investor characteristics to compare posting and non-posting investors with similar profiles. The matched results confirm that posting is associated with higher trading activity. Both IV and matching evidence strengthen the causal interpretation that social interaction on fintech platforms facilitates active investment behaviour.

The key question we address in this paper is the impact of socially driven transactions on investment returns.[5] Specifically, we find that higher posting frequency predicts improved fund returns in subsequent periods, with effects persisting over time. The magnitude of the impact declines gradually but remains statistically significant up to 6 months. These results are robust to alternative return definitions and hold under PSM. The persistence of the performance effect suggests that posting plays a role beyond contemporaneous sentiment expression. Instead, it reflects an adaptive process in which

investors refine their portfolio decisions through repeated interaction and delayed adjustment, consistent with a gradual form of social learning.

Next, we examine whether trading mediates posting's return effect. While posting significantly increases both trading frequency and volume, it but minimally affects turnover. Regression estimates show posting-trading interaction associates with short-term return declines that dissipate over time, while posting's direct return effect still remains positive. These findings suggest that trading induced by posting may initially incur transient frictions or learning costs. The consistent return gains point to a behavioural channel in which trading serves to implement insights acquired through social interaction.

Additionally, we assess whether the effect of posting varies with the type of content shared. Regression results reveal strong heterogeneity, posts that involve forward-looking information seeking, such as questions, are associated with the largest increases in trading activity and investment returns. Opinion posts also produce positive effects, though smaller in magnitude. In contrast, reactive content—such as comments or answers—has little effect on either trading or performance. The variations reveal that not all social interactions aid learning. The informational value of posting depends critically on its cognitive orientation and opportunities for feedback, clarification, and strategic adjustment.

Overall, we provide empirical evidence for a social learning mechanism operating through investor social interaction on fintech platforms. Posting not only shapes trading behaviour but also contributes to long-term performance improvement. This learning process is structured, selective, and shaped by both the intent of the engagement and the behavioural responsiveness of investors. Rather than reflecting mechanical attention or short-term noise, posting enables belief revision through information articulation, peer observation, and iterative portfolio adjustment.

Finally, we examine heterogeneity in the effectiveness of social learning across different investor groups. First, the performance impact of posting is more pronounced amongst investors who primarily hold index or stock funds, suggesting that portfolios with greater exposure to market volatility may be more responsive to socially acquired information. Second, we further find that the benefits of posting are concentrated amongst younger, risk-tolerant, and lower-wealth investors, as well as those with higher levels of digital engagement. These results suggest that the extent to which investors absorb and act on peer information varies systematically with their portfolio characteristics and behavioural traits, reinforcing the view that social learning is selective and context-dependent.

Our study contributes to several strands of research. First, there is ample evidence to suggest that social interaction amongst peers is crucial in investor decision-making (e.g., Huang et al. 2021; Frydman 2015; Ali-Rind et al. 2023; Kaustia and Knüpfer 2012; Heimer 2016; Wang et al. 2013; Zhang et al. 2022). For example, some studies have shown that there is a herd effect amongst investors in market participation and equity investment (e.g., Wermers 1999; Chang et al. 2000; Hong et al. 2005). In recent years, online social communities have shown an upward trend and become the main form of communication amongst investors. Therefore, online social plat forms are of great significance for investor decision-making (e.g., Barber and Odean 2002; Heimer and Simsek 2019; Ammann and Schaub 2021). Our paper utilizes data from individual mutual fund investor accounts in China to analyze how online posting behaviour affects the behaviour of fund investors, which is complementary to the literature.

Second, our paper is also related to the growing literature about the information value in social media. Despite a large amount of empirical literature, the results are at best mixed. Some studies show that the data generated by some large platforms, such Motley Fool, Seeking Alpha, Twitter, and Estimize, can be used to successfully predict future stock returns (e.g., Hirschey et al. 2001; Chen et al. 2014; Bartov et al. 2017, 2023), so online posts contain useful information (e.g., Crawford et al. 2017). However, some literature also shows that the information is full of noise (e.g., Tumarkin and Whitelaw 2001; Antweiler and Frank 2004; Das and Chen 2007; Kim and Kim 2014). Our paper considers that the information content of posts on the platform may vary, so we study the impact of information and noise in investment behaviours.

Third, our paper also contributes to empirical literature on the performance and behaviour of individual investors in the Chinese mutual fund market. Most of research in the mutual fund market centres around fund level or fund managers (e.g., Stein 2008; Crawford et al. 2017). In this paper, we shed light on the individual mutual fund investors and show that individual investors trade too frequently and that trading is detrimental to their wealth (e.g., Odean 1999; Barber and Odean 2000; Barber and Odean 2013). Fintech platforms have revolutionized the information acquisition and investment behaviour of individual investors, facilitating seamless access to information, significantly reducing transaction costs and stimulating residents' consumption (e.g., Farrell et al. 2022; Gong et al. 2023). However, it is also crucial to ponder whether Fintech genuinely enhances investment performance. This paper offers unique insights from the perspective of social interaction.

The remainder of the paper is organized as follows. In Section 2, we introduce the background of posting in the fintech platform. In Section 3, we explain the data and variables in our analysis. Section 4, we relate the investors characteristics to the online posts. In Section 5, we analyze the influence of posting on the trading behaviour and discuss robustness and endogeneity. Section 6 explores social learning through posting and trading. Section 7 discusses heterogeneity, and Section 8 concludes.

2. Posting in the Fintech Platform: Background and Theoretical Hypothesis

2.1. Investor Online Posts

Posting is a primary way for investors to engage in social interactions on the Fintech platform. They post to share their perspectives, comment on others' content, ask questions, and respond to inquiries. In general, the platform does not impose restrictions on the content that investors can share (except for illegal context).[6] Because the platform mainly provides fund trading services, most posts are related to financial and economic information.

To illustrate the process of posting, we give two examples in Figure 1. Panel A of Figure 1 demonstrates how investors share their opinions and comment on others' posts through the plat form. On the home page of the platform, users can enter the editing page by clicking on the floating blue plus sign to share their own opinions. Users can also leave comments after browsing others' posts. Panel B of Figure 1 illustrates how investors ask questions and provide answers on the platform. Investors can enter the discussion area through the home page and access the Q&A section. To ask a question, investors need to click on the blue plus sign to enter the asking page. If an investor wants to answer a specific question, she

can enter the question page and click on the blue “I want to answer” icon to enter the answering page, in which she can write down her answer and post it.

Panel A

Panel B

Fig.1. The process for posting. This figure illustrates the process of posting with examples. Panel A demonstrates how investors can share their opinions and comment on others’ posts through the platform. Panel B illustrates how investors can ask questions and provide answers on the platform. [Color figure can be viewed at wileyonlinelibrary.com]

2.2. The Motivation of Postin

There are three main reasons for investors to post on social platforms. First, investors post to engage in effective information interaction. Posting on social platforms encourages more investors to participate in discussions and responses, allowing them to receive valuable feedback (e.g., Stein 2008; Crawford et al. 2017). Therefore, posting could provide valuable information, as engaging in social learning enables investors to acquire more private information through communication with others (e.g., Bala and Goyal 1998; Wang et al. 2013; Blocher 2016). Second, investors may post to achieve self fulfilment because posters want to attract followers and hope to become opinion leaders by sharing attractive posts, showcasing their investment ability in expanding influence (e.g., Cao et al. 2024). Third, investors post to express and incite emotions, especially when their investment performance is poor. There are often many posts expressing anxiety or frustration about mutual fund managers. These posts are usually characterised by sharp language, containing a lot of personal emotions and noise. While information interaction is an effective way to acquire information, inciting emotions generates pure noise.

2.3. Theoretical Hypothesis

Investor posting on fintech platforms may shape trading and performance through two distinct but interconnected channels: the information (social learning) channel and the amplification (behavioural bias) channel. For example, Panel A of Figure 2 illustrates how investors share their operational notes and learn from the feedback of others, but in some cases, investors post to express emotion, attract attention, or reinforce pre-existing convictions without seeking substantive feedback. The post in Panel B is emotional noise with little valuable investment information.

1. Information channel: Social learning mechanism

The social learning theory provides a theoretical foundation for understanding how investor posting can improve investment outcomes. Bala and Goyal (1998) develop a formal model in which agents, situated in networks, revise their beliefs and actions by observing the behaviours and outcomes of peers. In financial markets, investors routinely face informational frictions and incomplete private signals, making them reliant on observable actions and communications within their social environment (e.g., Das and Chen 2007; Han and Yang 2013). In fintech platforms, the process of information aggregation has become more efficient, as these platforms facilitate the rapid and low-cost exchange of diverse viewpoints and investment strategies (e.g., Crawford et al. 2017; Farrell et al. 2022). When investors post questions, share operational experiences, or solicit opinions, they actively attract feedback from a broader community (e.g., Blocher 2016; Farrell et al. 2022).

Empirical evidence supports the positive role of social interaction. The transmission of peer opinions and forecasts through digital platforms enhances portfolio allocation, mitigates mis pricing, and leads to more consistent investment performance (e.g., Chen et al. 2014; Farrell et al. 2022). Moreover, investors who engage in structured, purposeful interactions—such as asking questions or contributing to substantive discussion— realize greater informational gains and performance improvements compared to those who limit themselves to passive observation (e.g., Huang et al. 2021; Ali-Rind et al. 2023). Literature

underscores that actively pursuing and integrating peer information via posting is a powerful mechanism for learning in digital financial markets, leading to Hypothesis 1:

H1. Posting improves investor performance by facilitating social learning.

2. Amplification channel: Behavioural biases mechanism

The behavioural bias amplification channel is grounded in the extensive literature of behavioural finance. Numerous studies demonstrate that individuals are prone to cognitive biases such as overconfidence, herding, and excessive trading, which can be exacerbated by social dynamics (e.g., Barber and Odean 2002; Barber and Odean 2002). Within online communities, posts that are motivated by emotion, affirmation-seeking, or attention rarely provide new information. Instead, these posts reinforce prior beliefs and amplify sentiment-driven behaviour, which may lead to persistent mispricing and increased volatility (e.g., Antweiler and Frank 2004; Wermers 1999; Tumarkin and Whitelaw 2001). The design of digital platforms can further magnify these effects, as algorithms tend to prioritize highly engaging or emotionally charged content, increasing the speed and breadth of information cascades (e.g., Kim and Kim 2014; Ammann and Schaub 2021; Pedersen 2022). Theoretical models of noisy social learning show that when public signals lack informational value or are redundant, feedback loops emerge that weaken the effectiveness of rational expectation formation and drive investors towards inefficient outcomes (e.g., Das and Chen 2007).

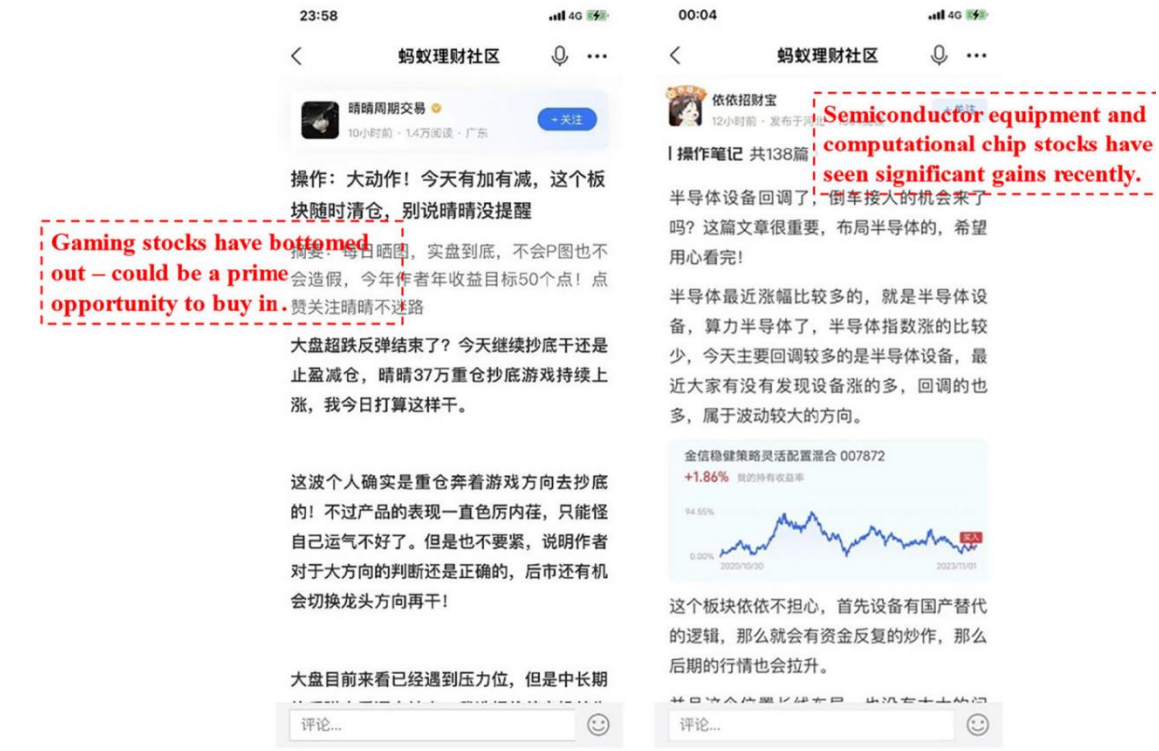
Empirical studies provide consistent evidence that attention-driven and emotion-driven social interaction correlates with inferior investment results and greater trading frictions (e.g., Heimer and Simsek 2019; Kaustia and Knüpfer 2012;Ali-Rind et al. 2023). These findings collectively indicate that, in the absence of effective informational filters and corrective mechanisms, posting can magnify behavioural biases and undermine overall investment performance. Therefore, we propose hypothesis 2:

H2. Posting decreases investor performance by amplifying behavioural biases.

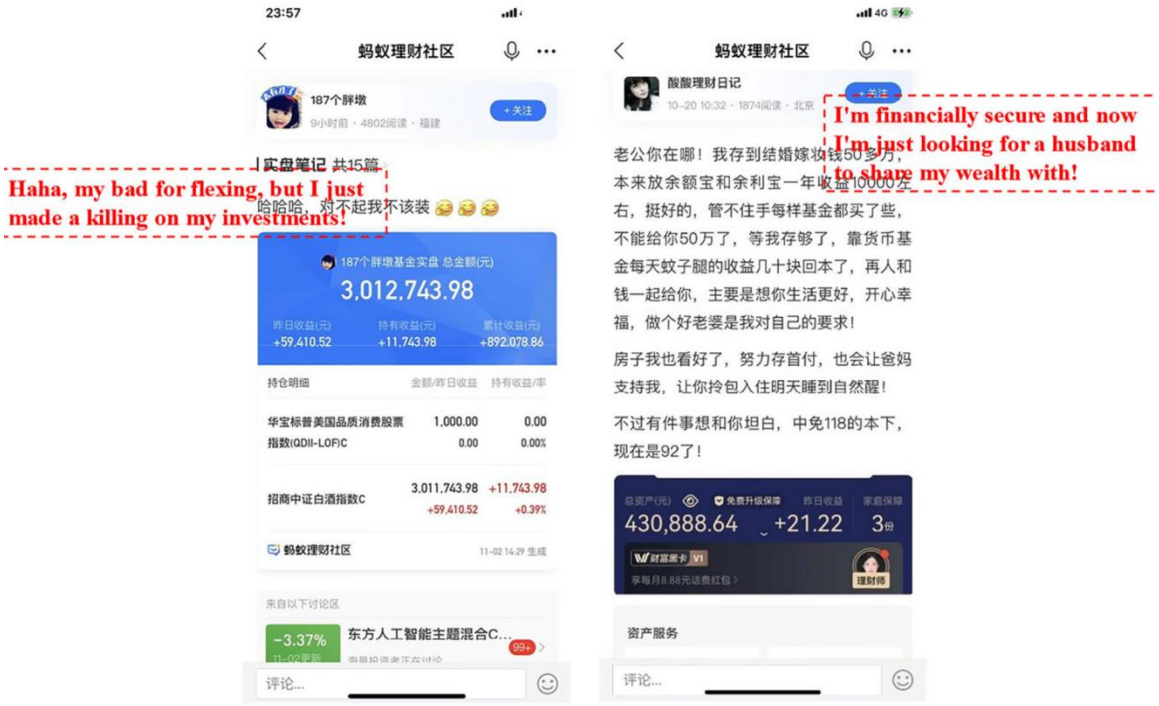
3. Data and Variables

3.1. Data

We employ proprietary data from a large-scale digital invest ment platform operated by Ant Fund, the largest third-party distributor of mutual funds in China.[7] The platform enables retail investors to execute fund transactions online and simul taneously engage in social interaction through various com municative features. Specifically, users can initiate discussions, respond to others' posts, and participate in investment-related exchanges on a semi-public forum. This integration of trans actional and social functions offers a distinct empirical en vironment for analyzing how peer-based interactions shape investor behaviour and performance in digital financial markets.[8]



Panel A



Panel B

Fig.2. Two posts as examples. This figure illustrates two posts as examples. Panel A shows investors displaying their operational notes and learning new information through feedback from other investors. Panel B shows noise that releases emotions. [Color figure can be viewed at wileyonlinelibrary.com]

Table 1
Variable definition.

	Variable	Definition
Social interaction	*Total Number of Posts*	Total number of posts published by the investor during the month
	Total Characters of Posts	Total number of characters published by the investor during the month
	Number of Opinions Posted	Number of opinions published by the investor during the month
	Number of Comments Posted	Number of comments published by the investor during the month
	Number of Questions Posted	Number of questions published by the investor during the month
	Number of Answers Posted	Number of answers published by the investor during the month
	Posting Dummy	A dummy variable for measuring whether to post or not
Trading behaviours	*Total Number of Trades*	Total number of mutual fund transactions during the month
	Total Amount of Trades	Total amount of mutual fund transactions during the month
	Number of Fund Purchase	Total number of mutual fund purchases during the month
	Amount of Fund Purchase	Total amount of mutual fund purchases during the month
	Number of Fund Redemption	Total number of mutual fund redemptions during the month
	Amount of Fund Redemption	Total amount of mutual fund redemptions during the month
	Turnover	*Amount of Purchase* divided by *Fund Holdings*
Investment performance	*Return*	The monthly return, calculated as: $\frac{\text{Absolute Return}}{\text{Fund Holding}}$
	Alpha	For each investor, we perform a time series regression of their monthly returns over a 24-month period against the market returns. The intercept from this regression represents the investor's alpha, which captures the excess return unexplained by market movements. $\text{Ret}_{i,t} = \text{Alpha}_i + \beta_i \text{Mktrf} + \epsilon_{i,t}$
	Absolute Return	The cumulative return of mutual fund returns held during the month
Fund allocation	*Fund Holdings*	The monthly average mutual fund holding of individual investors in Ant Fund
	Proportion of Bond Fund	The proportion of bond funds in mutual fund
	Proportion of Hybrid Fund	The proportion of hybrid funds in mutual fund
	Proportion of Stock Fund	The proportion of stock funds in mutual fund
	Proportion of Index Fund	The proportion of index funds in mutual fund
Individual characteristics	*Age*	
	Gender	A female dummy variable

(Continues)

Variable	Definition
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.
Years of App Usage	The year since the investor registered App
Browsing	The monthly aggregate attention input that investor spend on the fintech platform

Note: This table presents the definition of our variables.

In detail, our data set includes a balanced monthly panel of 11,715 anonymized investor accounts covering the period from April 2020 to March 2022, with a total of 281,160 investor-month observations. All data are aggregated at the monthly level, and the units of observation are at the investor account level.[9] Investment returns are reported at the account level and reflect the average performance across all positions. Social interaction is recorded through structured metrics including the number of opinions, comments, questions, and answers. However, the data set does not include the textual content of these interactions, which limits the application of content-based or semantic analysis.[10]

3.2. Variables

Because each post is recorded by the platform, we can obtain data on the number of posts made by each investor, including four types of posts, which are opinions, comments, questions, and answers. These four types of posts are aggregated monthly to obtain the investor's monthly posting frequency.[11] We have the total numbers of various posts and individual counts for posts, resulting in five key independent variables. In addition, we also design dummy variables to indicate whether a post is made or not.

Our data set includes monthly information on investors' fund trading activities, such as the number of transactions and the trading amounts. We use the total amount of funds purchased and redeemed by an investor within a month to measure the total trading and then examine investor fund trading behaviour from three perspectives: total trading, fund purchase, and fund redemption. Therefore, we have six variables that describe trading behaviour, including *Total Number of Trades, Total Amount of Trades, Number of Fund Purchase, Amount of Fund Purchase, Number of Fund Redemption, Amount of Fund Redemption.*

We obtain data on monthly fund investment returns and the fund holdings of investors. To mitigate the impact of investors purchasing and redeeming funds in the middle of the month on return calculations, our paper calculates the investment return by dividing the earning at the end of the month by the average amount of fund holding during that month. In addition, we calculate the *Turnover by dividing the Amount of Fund Purchase* by the logarithm of the total amount of funds held by investors.

In the regression model, we employed two-way fixed effects. To further mitigate omitted variable bias arising from time-varying and individual-specific factors, we controlled for key observable variables that influence both investors' trading behaviour and posting behaviour, including *Return,* the investment return of investor i in month t; *Fund Holdings*, the logarithm of total amount of funds held by investor i in month t. *Browsing*, the total time spent by investors browsing information in the Ant Fund. Table 1 reports the variable definitions.

3.3. Summary Statistics

Table 2 provides summary statistics of the key variables in our analysis. Panel A reports descriptive statistics for investor online posts, summarized monthly and cumulatively. Our first observation is that only a few investors post on the platform. On average, investors post 9.20 times per month. We also report the number of posts by type. On average, investors share opinions 3.86 times per month, comment 5.24 times per month, ask questions 0.02 times per month, and provide answers 0.09 times per month.

Panel B describes investor trading behaviours, and we find that investors on the Fintech platform are quite active in trading. On average, all investors trade 54.42 times per month, with an average of 45.45 purchase transactions and 8.97 redemption transactions per month. In terms of transaction amounts, all investors have an average monthly fund transaction amount of 80,437.28 RMB, with an average monthly purchase amount of 41,678.57 RMB and an average monthly redemption amount of 38,758.71 RMB.

Panel C describes the trading characteristics. There is significant variance amongst investors, both in terms of returns and turnovers. On average, investors experience a monthly investment return of 1% and a monthly investment turnover of 0.38.

Panel D provides information on investors' personal characteristics. Most investors are relatively young, with an average age of 38.86 years. Female investors account for 29% of the sample. On average, investors in the community have been using the Fintech platform for 8.74 years and have a moderate risk tolerance (with risk tolerance ranging from 1 as the lowest to 5 as the highest). The average fund holding of investors is 149,391.40 RMB.

4. Who Are Active in Posting?

4.1. Main Results

To better understand the behaviour of investors participating in social interactions, we first study which types of investors express themselves more actively by posting on the platform. Specifically, we estimate the following cross-sectional regression at the account level:

$$Post_i = \alpha + x_i'\beta + \epsilon_i, \quad (1)$$

where $Post_i$ includes the total number of posts, the number of opinions posted, the number of comments posted, the number of questions posted, and the number of answers posted on the platform by account holder i in whole sample period. We take the logarithm of these variables as dependent variables. We control two groups of dependent variables x'_i. The first group includes investment variables: Total Amount of Fund Trades, the logarithm of average monthly amount of fund trades by investors; Fund Holdings, the logarithm of average monthly amount of funds held by investors; Monthly Return, the average monthly return of investors. The second group includes demographic characteristics: *Age*, the age of the investor; *Gender*, a female dummy that equals1 if investor is female; *Risk-Tolerance*, the investor's risk-tolerance level evaluated by the App ranking from 1to5; *Years of App Usage*, the years since the investor registered App. We take the average of all the control variables during the whole sample period and control them in Equation(1).

Table 2
Summary statistics

Variable name	Count (1)	Mean (2)	Std (3)	Min (4)	25%Pct (5)	Median (6)	75%Pct (7)	Max (8)
Panel A. Social interaction								
Total Number of Posts	281,160	9.20	100.98	0.00	0.00	0.00	2.00	10,268.00
Number of Opinions Posted	281,160	3.86	30.99	0.00	0.00	0.00	1.00	5199.00
Number of Comments Posted	281,160	5.24	85.06	0.00	0.00	0.00	0.00	10,132.00
Number of Questions Posted	281,160	0.02	0.22	0.00	0.00	0.00	0.00	32.00
Number of Answers Posted	281,160	0.09	4.83	0.00	0.00	0.00	0.00	1562.00
Posting Dummy	281,160	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Total Number of Posts (Cumulative)	11,715	220.75	1890.32	0.00	1.00	14.00	86.50	101,849.00
Number of Opinions Posted (Cumulative)	11,715	92.53	562.79	0.00	0.00	6.00	41.00	28,089.00
Number of Comments Posted (Cumulative)	11,715	125.80	1573.96	0.00	0.00	4.00	32.00	87,896.00
Number of Questions Posted (Cumulative)	11,715	0.38	2.17	0.00	0.00	0.00	0.00	119.00
Number of Answers Posted (Cumulative)	11,715	2.04	57.75	0.00	0.00	0.00	0.00	3416.00
Panel B. Trading behaviours								
Total Number of Trades	281,160	54.42	132.06	0	6.00	21.00	55.00	7356.00
Total Amount of Trades	281,160	80,437.28	214,999.80	0	5423.41	24,087.53	75,549.09	12,744,600.00
Number of Fund Purchase	281,160	45.45	117.63	0	4.00	16.00	44.00	7041.00
Amount of Fund Purchase	281,160	41,678.57	111,230.50	0	2400.00	12,110.17	39,499.82	6,411,895.00
Number of Fund Redemption	281,160	8.97	23.42	0	0.00	3.00	9.00	1661.00
Amount of Fund Redemption	281,160	38,758.71	113,885.30	0	0.00	7871.07	34,166.75	7,716,134.00
Turnover	275,735	0.38	0.59	0.00	0.05	0.19	0.47	1.00
Panel C. Investment performance								
Return (%)[a]	275,735	0.01	0.07	−15.18	−0.03	0.01	0.05	1.21
Panel D. Individual characteristics								
Age	11,715	38.86	10.18	20.00	31.00	37.00	46.00	81.00
Gender	11,715	0.29	0.45	0.00	0.00	0.00	1.00	1.00
Risk-Tolerance	11,715	3.13	1.16	−2.00	2.00	3.00	4.00	5.00
Years of App Usage	11,715	8.74	3.07	3.00	6.00	8.00	11.00	18.00
Fund Holdings	281,160	149,391.40	258,447.20	0.00	29,369.32	74,272.86	169,076.80	7,129,705.00
Browsing	281,160	145.76	272.65	0.00	15.22	55.26	156.08	11,021.51

Note: This table reports summary statistics of variables. For each panel, we report the count (Count), mean (Mean), the standard deviation (Std), minimum (Min), the 25th, 50th, 75th percentiles, and maximum (Max) of the variables. Panel A–D report characteristics of posts, trading behaviour, investment return and characteristics of the fund investors, respectively.

[a]In especially, the denominator in the calculation of the rate of return is Fund Holding on the month basis, while the return refers to the cumulative return achieved during that month, we are unable to observe the specific day when the return is generated or track daily changes in fund holdings, so the max and min of the return (%) have no reference value. In Panel B, we replace 1%pct for min, and 99%pct for max.

Table 3 reports the regression results of Equation (1) in which we link investor characteristics with the number of posts. Column (1) displays several interesting findings. First, the more investors trade, the more actively they post in online community. Second, the higher amount of funds held by investors, the lower their posting frequency. Third, young individuals are more inclined to post on Fintech platform. Fourth, male investors exhibit a stronger desire to express themselves, posting 40.1% more than female investors. Fifth, investors with higher risk tolerance are more inclined to participate in online communities. For each level of risk tolerance increase, the frequency of posting increases by 13.5%. Finally, in column (4), investors with lower returns and older investors tend to ask more questions.[12]

Taken together, our findings indicate that social interaction on the platform is systematically influenced by heterogeneity in investors' preferences, behaviours, and informational needs. Rather than being a neutral or uniformly distributed feature, posting reflects selective engagement driven by underlying cognitive and portfolio characteristics. This leads to our core empirical question: To what extent does posting activity translate into meaningful changes in trading behaviour and investment outcomes? We now examine whether such interactions serve merely expressive purposes or function as mechanisms for information acquisition and adaptive learning.

5. Baseline Result: How Does Posting Affect Trading Behaviour?

In this section, we focus on the impact of investor posting through online community on their trading behaviour and investment returns.

5.1. Baseline Results

Investors can browse the posts and engage in actions such as liking, sharing, commenting, and answering. The feedback from other community participants on the posts further influences investor behaviour. Therefore, both the way of posting and the feedback from other community participants affect investors' trading behaviour. In our empirical analysis, we estimate the following panel regression:

$$Fund\_Trade_{i,t+1} = \beta_0 + \beta_1 \quad Posting_{i,t} + \beta' x_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{2}$$

Table 3
Investor portrait and post.

Variable name	Total number of posts (1)	Number of opinions posted (2)	Number of comments posted (3)	Number of questions posted (4)	Number of answers posted (5)
Total Amount of Trades	0.616***	0.534***	0.541***	0.042***	0.035***
	(0.025)	(0.023)	(0.023)	(0.005)	(0.006)
Fund Holdings	−0.427***	−0.365***	−0.372***	−0.027***	−0.019***
	(0.028)	(0.026)	(0.026)	(0.005)	(0.006)
Return	−3.450	−3.359	−1.783	−0.936***	−0.549
	(4.494)	(4.414)	(3.479)	(0.311)	(0.481)
Age	−0.011***	−0.010***	−0.010***	0.002***	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)
Gender	−0.401***	−0.513***	−0.225***	−0.012	−0.011
	(0.044)	(0.039)	(0.040)	(0.009)	(0.009)
Risk-Tolerance	0.135***	0.131***	0.095***	0.016***	0.019***
	(0.020)	(0.018)	(0.018)	(0.004)	(0.004)
Years of App Usage	−0.004	−0.015**	0.004	−0.002	0.002
	(0.007)	(0.006)	(0.006)	(0.001)	(0.002)
Constant	1.380***	1.041***	0.683***	−0.080**	−0.116**
	(0.221)	(0.204)	(0.202)	(0.041)	(0.049)
Observation	11715	11715	11715	11715	11715
R-squared	0.080	0.084	0.064	0.011	0.008

Note: This table reports regression results on the relation between investor portrait and post. We estimate the following cross-sectional regression: $Post_i = \alpha + x_i'\beta + \epsilon_i$.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

where $Fund\ Trade_{i,t+1}$ is the average investment behaviour of investor i from month $t + 1$. The dependent variables describing investment behaviour contain: Total Number of Trades,

Total Amount of Trades, Number of Fund Purchase, Amount of Fund Purchase, Number of Fund Redemption, Amount of Fund Redemption. In the regression, all dependent variables are logarithmic. The key independent variable ($Posting_{i,t}$) is *Total Number of Posts*, which is the logarithm of the total number of posts shared by investor i in month t. The control variables ($x_{i,t}$) contain *Return, Fund Holdings, Browsing*. α_i is the investor i's fixed effect, and γ_t is the year-month fixed effect. $\epsilon_{i,t}$ is the residual.[13] Table 4 reports the estimation results of the total number of posts by investors on the trading. In Column (1), we find that the total number of posts by investors significantly influences their trading frequency. In period $t + 1$, after including control variables and fixed effects, 1% increase in posting leads to a significant 0.035% increase in the monthly total trading frequency. In Column (2), We find that the total number of posts significantly increases investors' monthly total trading amount. To be specific, 1% increase in posts by investors leads to a 0.036% increase in the total trading amount in the next month.

Next, we differentiate investors' trading behaviour into purchase and redemption. Column (3) of Table 4 present the estimated results of the impact of investors' posting frequency on their purchase frequency. We find that investors' posting frequency has a significant positive impact on their purchase frequency. Similarly, we change the dependent variable to purchase amount and present the regression results in Column (4). In general, the results are qualitatively the same as the previous ones.

Moreover, we further estimate the impact of investor posting on fund redemption. Column (5) presents the estimated results for the total number of posts on investor redemption frequency. We find that the number of posts made by investors significantly increases their redemption frequency, at $t + 1$, for every 1% increase in investors' posts at time t, the number of redemption transactions increases by 0.037%. Similarly, we replace the dependent variable with redemption amount, and the results are reported in Column (6). The empirical results show that the total number of posts has a significant positive impact on investor redemption amounts.

Furthermore, we substitute the independent variable to the Total Characters of Posts, which is the logarithm of the total number of characters shared by investor's postings in month t. Table 5 shows the empirical results based on the posting characters, at $t + 1$, for every 1% increase in investors' posts at time t, the total number of transactions increases by 0.017%, and the total amount of transactions increases by 0.020%, the number and amount of purchasing increases by 0.017% and 0.025%, and the number and amount of redemption increases by 0.017% and 0.050%.

Our empirical results indicate that posting behaviour has a positive impact on investor trading. Posting on the platform can motivate investors to actively participate in financial activities and manage investments. This positive impact may come from additional information obtained by investors from social interactions or from the amplification of irrational behaviour influenced by the emotions of others.

5.2 Robustness Test

To further test the robustness of the aforementioned empirical findings, we conduct three sets of robustness tests: replacing the sample, independent variable, and dependent variable. The results from these tests consistently show that postings amongst retail investors on social platforms drive more active trading.

Table 4
The impact of the number of posting on fund trading.

Variable name	Total number of trades (1)	Total amount of trades (2)	Number of fund purchase (3)	Amount of fund purchase (4)	Number of fund redemption (5)	Amount of fund redemption (6)
Total Number of Posts	0.035***	0.036***	0.038***	0.049***	0.037***	0.092***
	(0.004)	(0.009)	(0.004)	(0.010)	(0.003)	(0.012)
Browsing	0.201***	0.362***	0.200***	0.424***	0.134***	0.429***
	(0.003)	(0.007)	(0.003)	(0.008)	(0.002)	(0.009)
Return	0.015***	0.038***	0.016***	0.045***	0.007***	0.037***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.000)	(0.002)
Fund Holdings	0.191***	0.765***	0.126***	0.494***	0.207***	1.062***
	(0.005)	(0.012)	(0.005)	(0.013)	(0.005)	(0.017)
Constant	−0.044	−0.629***	0.515***	1.250***	−1.396***	−6.508***
	(0.051)	(0.125)	(0.051)	(0.136)	(0.050)	(0.183)
Investor fixed effects	YES	YES	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES	YES	YES
Observation	264,385	264,385	264,385	264,385	264,385	264,385
R-squared	0.144	0.124	0.107	0.084	0.117	0.104

Note: This table reports regression results on the relation between posting and fund trading. We estimate the following two-way fixed panel regression: $Fund\_Trade_{i,t+1} = \beta_0 + \beta_1 \quad Posting_{i,t} + \beta' x_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$.
Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5
The impact of the character of posting on fund trading.

Variable name	Total number of trades (1)	Total amount of trades (2)	Number of fund purchase (3)	Amount of fund purchase (4)	Number of fund redemption (5)	Amount of fund redemption (6)
Total Characters of Posts	0.017***	0.020***	0.017***	0.025***	0.017***	0.050***
	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)	(0.006)
Browsing	0.202***	0.361***	0.200***	0.424***	0.135***	0.429***
	(0.003)	(0.007)	(0.003)	(0.008)	(0.002)	(0.009)
Return	0.015***	0.038***	0.016***	0.045***	0.008***	0.037***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.000)	(0.002)
Fund Holdings	0.191***	0.765***	0.126***	0.495***	0.208***	1.062***
	(0.005)	(0.012)	(0.005)	(0.013)	(0.005)	(0.017)
Control Variables	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES
Investor Fixed Effects	YES	YES	YES	YES	YES	YES
Year-Month Fixed Effects	YES	YES	YES	YES	YES	YES
Observation	264,385	264,385	264,385	264,385	264,385	264,385
R-squared	0.144	0.124	0.107	0.084	0.117	0.104

Note: This table reports regression results on the relation between posting (the number of posting characters) and fund trading. We estimate the following two-way fixed panel regression:

$$Fund\_Trade_{i,t+1} = \beta_0 + \beta_1 \quad Posting_{i,t} + \beta' x_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}.$$

Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2.1 Only Consider Investors Who Have Posted

Some investors may rely on alternative sources of information outside the platform, and as a result, they do not engage in social interactions on the fintech platform. We exclude those investors who have never posted, focusing only on those who have posted for further estimation. Panel A of Table 6 presents empirical results after adjusting the sample. After excluding non-posting investors, we observe an increase in the regression coefficient, suggesting a stronger economic effect of social interaction on trading behaviour amongst investors who post.

5.2.2 Replace the Independent Variable

In the meantime, we further substitute independent variables with dummy variables, specifically Posting Dummy, to assess the robustness of our benchmark regression results. Panel B of Table 6 presents the results when using the dummy variable as an independent variable. Our findings show that, compared to investors who have never posted on the platform, those who post demonstrate significantly higher trading frequency and amounts, along with increased purchase and redemption activities. These results reaffirm the robustness of our benchmark regression analysis.

5.2.3 Replace the Dependent Variable

In addition, we substitute the dependent variable with Turnover, a proxy for trading activity, defined as the ratio of the total trading amount to fund assets. Panel C of Table 6 presents the results for Turnover. Our findings indicate that both the number of posts and the total character count of these posts significantly increase fund trading. Furthermore, when we mitigate potential biases from abnormal turnover rate samples (Columns (3) and (4) winsorized at the 95th percentile), the results remain consistent with our benchmark regression outcomes.

5.3 Endogeneity

A potential concern in our empirical framework is that unobserved investor characteristics may simultaneously affect both the intensity of social interaction and trading behaviour, leading to omitted variable bias. For instance, intrinsic traits such as risk preference, financial literacy, or digital engagement may influence an investor's propensity to post as well as their likelihood of trading actively. Moreover, there is a possibility of reverse causality: investors who trade more frequently may be more inclined to participate in social discussions or seek validation for their trading decisions, which could bias the estimated effect of posting.[14] Therefore, to tackle endogeneity issues, we employ both IV and PSM methods.

5.3.1 IV Estimation

First, we implement the IV approach. Specifically, we use three instrument variables based on group-level posting activity: (1) Same Personality, defined as the average number of posts by investors sharing similar demographic and behavioural characteristics; (2) Same City, based on the average number of posts by investors residing in the same city; and (3) Same Personality and City, calculated as the average number of posts by those who share both personal traits and geographic location with the focal investor. The group average excludes the focal investor, ensuring instrument externality to its own behaviour.

Table 6
Robustness test.

Panel A. Robustness test of replacing sample

Variable name	Total number of trades (1)	Total amount of trades (2)	Number of fund purchase (3)	Amount of fund purchase (4)	Number of fund redemption (5)	Amount of fund redemption (6)
Total Number of Posts	0.035***	0.059***	0.036***	0.064***	0.034***	0.099***
	(0.006)	(0.012)	(0.006)	(0.014)	(0.005)	(0.018)
Control variables	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES	YES	YES
Observation	93,776	93,776	93,776	93,776	93,776	93,776
R-squared	0.097	0.100	0.068	0.057	0.091	0.083

Panel B. Robustness test of replacing independent variable

Variable name	Total number of trades (1)	Total amount of trades (2)	Number of fund purchase (3)	Amount of fund purchase (4)	Number of fund redemption (5)	Amount of fund redemption (6)
Posting Dummy	0.077***	0.123***	0.079***	0.154***	0.065***	0.211***
	(0.006)	(0.016)	(0.007)	(0.018)	(0.005)	(0.023)
Control variables	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES
Year-month fixed Effects	YES	YES	YES	YES	YES	YES
Observation	264,385	264,385	264,385	264,385	264,385	264,385
R-squared	0.144	0.125	0.107	0.084	0.117	0.104

Panel C. Robustness test of replacing dependent variable

	Turnover			
	Full sample		95% Winsorized	
Variable name	(1)	(2)	(3)	(4)
Total Number of Posts	0.020***		0.020***	
	(0.003)		(0.003)	
Total characters of Posts		0.006***		0.006***
		(0.001)		(0.001)
Control variables	YES	YES	YES	YES
Constant	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES
Observation	263,200	263,200	263,200	263,200
R-squared	0.045	0.045	0.045	0.045

Note: This table reports results of robustness test. In Panel A, we replace the full sample to the sample that has posted. In Panel B, we use *Posting_Dummy* as the independent variable. In Panel C, we use *Turnover* as the dependent variable. Other settings are consistent with Table 4. Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
IV estimations.

Panel A. IV-1 (same personality) results

	IV = Same group posts						
	First-stage	Second-stage					
Variable name	Total number of posts (1)	Total number of trades (2)	Total amount of trades (3)	Number of fund purchase (4)	Amount of fund purchase (5)	Number of fund redemption (6)	Amount of fund redemption (7)
Same Personality	0.875***						
	(0.017)						
Total Number of Posts		0.266***	0.440***	0.274***	0.515***	0.272***	0.833***
		(0.019)	(0.036)	(0.019)	(0.039)	(0.016)	(0.053)
Constant	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES
Year-month fixed effect	YES	YES	YES	YES	YES	YES	YES
Investor fixed effect	YES	YES	YES	YES	YES	YES	YES
F-test	2696.4***						
DWH test		17.760***	7.959***	24.051***	17.039***	41.515***	29.659***
R-squared	0.032						
Observations	264,385	264,385	264,385	264,385	264,385	264,385	264,385

Panel B. IV-2 (same city) results

	IV = Same city posts						
	First-stage	Second-stage					
Variable name	Total number of posts (1)	Total number of trades (2)	Total amount of trades (3)	Number of fund purchase (4)	Amount of fund purchase (5)	Number of fund redemption (6)	Amount of fund redemption (7)
Same City	0.953***						
	(0.016)						
Total Number of Posts		0.236***	0.660***	0.216***	0.602***	0.252***	1.071***
		(0.018)	(0.036)	(0.018)	(0.039)	(0.014)	(0.053)
Constant	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES
Year-Month fixed effect	YES	YES	YES	YES	YES	YES	YES
Investor fixed effect	YES	YES	YES	YES	YES	YES	YES
F-test	3612.8***						
DWH test		6.240**	78.193***	2.917*	39.755***	25.796***	99.659***
R-squared	0.032						
Observations	264,385	264,385	264,385	264,385	264,385	264,385	264,385

Panel C. IV-3 (same personality and city) results

	IV = Same group & city posts						
	First-stage	Second-stage					
Variable name	Total number of posts (1)	Total number of trades (2)	Total amount of trades (3)	Number of fund purchase (4)	Amount of fund purchase (5)	Number of fund redemption (6)	Amount of fund redemption (7)
Same Personality and City	0.929***						
	(0.003)						
Total Number of Posts		0.216***	0.385***	0.390***	0.390***	0.217***	0.648***
		(0.004)	(0.007)	(0.007)	(0.007)	(0.003)	(0.010)

(Continues)

Panel C. IV-3 (same personality and city) results							
	IV = Same group & city posts						
	First-stage	Second-stage					
Variable name	Total number of posts (1)	Total number of trades (2)	Total amount of trades (3)	Number of fund purchase (4)	Amount of fund purchase (5)	Number of fund redemption (6)	Amount of fund redemption (7)
Constant	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES
Year-month fixed effect	YES	YES	YES	YES	YES	YES	YES
Investor fixed effect	YES	YES	YES	YES	YES	YES	YES
F-test	9.241***						
DWH test		84.303***	66.187***	33.923***	33.923***	301.618***	163.608***
R-squared	0.427						
Observations	264,385	264,385	264,385	264,385	264,385	264,385	264,385

Note: This table reports the IV estimations results, we have three instrumental variables, first is *Same Personality*, that is the number of posts of other investors' who have same personality. Second is *Same City*, that is the number of posts of other investors' who are located in same city. Third is *Same Personality and City*, that is the number of posts of other investors' who have same personality and are located in same city. Standard errors are clustered at the investor level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Our instrumental variables are grounded in behavioural and informational foundations that satisfy both correlation and exogeneity. First, investors who share similar demographic and behavioural characteristics—such as age, asset holdings, risk tolerance, and platform experience—tend to exhibit comparable levels of financial literacy, digital engagement, and social participation. As such, the average posting behaviour of these demographically similar peers is likely to be highly correlated with an individual investor's own inclination to post, satisfying the relevance condition (e.g., De Giorgi et al. 2010). Likewise, geographic proximity further strengthens this correlation, as investors from the same city may be exposed to similar local economic news, fintech adoption patterns, or social norms surrounding investment behaviour (e.g., Hong et al. 2005; Pedersen 2022). Second, while peer posting behaviour reflects common group-level tendencies towards social interaction, it is unlikely to directly influence any single investor's fund trading activity except through their own posting behaviour. In particular, we compute group-level posting averages by excluding the investor itself, thereby mitigating correlation.

To construct these instrument variables, we first divide the full sample into subgroups along four investor-level dimensions: age ([18, 30], [30, 40], [40, 50], [50, 60], [60+]), asset scale ([0, 20k], [20k, 50k], [50k, 100k], [100k, 200k], [200k+]), years of platform usage ([0, 5], [5, 8], [8, 10], [10, 12], [12+]), and risk tolerance (ranked 1 to 5). For each subgroup, we compute the average number of posts made by other investors within the same category, either in demographic space, geographic space, or both. These subgroup-level averages serve as instrument variables in a two-stage least square (2SLS) estimation.

Table 7 reports the results. Across all specifications and instrument sets, the first-stage regressions show strong statistical relevance, with F-statistics well above the conventional threshold of 10. In the second stage, posting remains positively and significantly associated with all trading outcomes. The magnitude of the estimated effects is consistent across Panels A through C. Durbin-Wu-Hausman tests reject the null hypothesis of exogeneity, confirming that OLS estimates are likely biased and that the IV strategy provides a more consistent estimate of the causal effect. Together, the results reinforce our main conclusion that posting behaviour plays a central role in shaping trading activity on fintech platforms.

5.3.2 PSM Approach

To further mitigate concerns of selection bias arising from observable heterogeneity, we employ a PSM strategy to re-estimate the effect of posting on investor trading.[15] The matching procedure relies on a set of investor-level covariates: Age, Gender, Risk-Tolerance, Years of App Usage, Fund Holdings, Browsing reflecting demographic traits, behavioural risk orientation, and platform usage patterns. These variables are chosen to capture heterogeneity in investor sophistication, attention to the platform, and baseline financial behaviour, all of which may influence both posting and trading activity. Matching is conducted using nearest-neighbour matching with caliper adjustment.

Panel A of Table 8 reports the results of the covariate balance test. Before matching, there exist notable differences in the distribution of several variables between the treated and control groups, most notably in age and platform usage. After matching, standardized mean differences across all five co-variates fall below 10%.[16] This improvement allows us to compare treated and control investors with similar observable characteristics.

Table 8

PSM approach results.

Panel A. Balancing test of PSM: mean difference and standardized mean difference (%)

Variable name	Before or after matching (1)	Mean difference (2)	Mean difference (%) (3)	Standardized mean difference across covariates (%) (4)
Age	BM	−0.961	−2.584	10.234
	AM	0.190	0.527	−2.043
Gender	BM	−0.144	−34.450	30.633
	AM	0.020	7.874	−4.535
Risk-Tolerance	BM	0.237	7.942	−21.142
	AM	−0.031	−0.953	2.778
Years of App Usage	BM	−298.495	−8.278	25.676
	AM	22.560	0.687	−1.995
Ln (1+Fund Holdings)	BM	1.348	14.412	−50.054
	AM	−0.120	−1.109	0.470
Ln (1+Browsing)	BM	1.957	479.657	−126.266
	AM	0.048	2.072	−2.485

Panel B. Post-matching treatment effects

Outcome variable	Posting group mean (1)	Non-posting group mean (2)	Difference (ATT) (3)	Std error (4)	*T*-value (5)
Total Number of Trades	2.572	2.300	0.271	0.004	75.833***
Total Amount of Trades	8.499	7.877	0.622	0.009	73.084***
Number of Fund Purchase	2.332	2.084	0.247	0.004	67.269***
Amount of Fund Purchase	7.581	6.993	0.589	0.009	65.917***
Number of Fund Redemption	1.200	0.946	0.253	0.003	99.753***
Amount of Fund Redemption	6.123	5.114	1.008	0.011	94.073***
Return	1.110	1.077	0.032	0.010	3.260***
Observations			333,718		

Note: This table presents PSM estimation results. Panel A reports the mean values of covariates for posting and no posting investors before and after propensity score matching. Panel B presents the PSM estimates of the average treatment effect on the treated (ATT) for posting on trading and performance. |SMD | < 10% indicates no significant difference in both groups. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The post-matching treatment effect estimates are presented in Panel B of Table 8. Posting is consistently associated with greater trading intensity across all measures, including the total number and amount of fund transactions, purchases, and redemptions, and the differences are economically meaningful and statistically significant. These results lend further support to our main findings, suggesting that posting captures a more active mode of platform engagement and may reflect greater responsiveness to available information.

6. Social Learning Through Posting and Trading

We now examine whether the relationship between posting and investor behaviour can be explained by a social learning mechanism. Specifically, we explore three aspects of this process. First, we test whether posting is linked to persistent performance improvements, consistent with learning rather than short-term reaction. Second, we evaluate whether trading acts as a channel through which information gathered via posting is incorporated into decision-making. Third, we examine whether the impact of posting varies with the content, assessing whether the cognitive intent behind interaction influences its effectiveness.

6.1. The Positive Impact of Posting on Return

We begin by evaluating the relationship between posting and subsequent investment performance.[17] Table 9 shows that the frequency of posting is positively associated with future returns. A one-unit increase in the logarithm of total posts predicts a 0.07% increase in return in month t+1, statistically significant at the 5% level. The effect gradually declines to 0.06% at t + 3 and stabilizes at 0.04% at t+6, both significant at the1%level. These results suggest that posting has a persistent and economically meaningful association with investor performance over time.

Furthermore, we replace the dependent variable with Absolute Return and Alpha (cross-sectional in Panels A and B of Table 10) and find that the positive relationship remains consistent across specifications.[18] Moreover, the PSM analysis in Panel B of Table 8 confirms that posting investors earn significantly higher monthly returns than matched non-posters, with an average treatment effect of 3.2%. Together, the regression and matching evidence support the conclusion that posting is linked to improved performance, rather than being driven by unobserved selection or model-specific artefacts.

These findings are consistent with the hypothesis (H1) that posting facilitates a form of gradual learning through social-mediated interaction. On Fintech platforms, posting is not merely expressive but serves as a mechanism for articulating provisional beliefs, eliciting informal peer feedback, and iteratively refining investment strategies. The act of publicly expressing one's views invites evaluation, which may prompt investors to reassess their assumptions or adjust their portfolio allocations accordingly. This feedback driven process contributes to a slow accumulation of informational gains, particularly in an environment where formal financial advice may be limited or costly. Moreover, the semi-public structure of these platforms allows investors to tap into distributed signals across a broad user base, thereby mitigating the influence of idiosyncratic noise or overconfidence. The presence of modest but statistically robust return improvements is consistent with evidence from Huang et al. (2021), who document performance gains amongst communicative

investors. Overall, posting serves as both communicative and cognitive functions in shaping investment quality.

6.2 Trading as a Learning Mechanism

While frequent trading may superficially appear detrimental to performance (suggesting overreaction or excess activity), our findings reveal no contradiction between trading intensity and returns. Rather, they represent complementary dimensions of a learning process: Social interaction via posting enables investors to formulate expectations, integrate feedback, and refine beliefs; trading then behaviourally implements these evolving judgements through portfolio adjustments.

Although posting is associated with significantly higher trading activity across various dimensions (such as purchase frequency, redemption activity, and trade volume), the effect on turnover is relatively modest and short-lived. As shown in Table 11, posting has a statistically significant impact on turnover in the first 2 months following the interaction, but this effect disappears by t +3.[19] This suggests that investors do not engage in excessive or persistent portfolio reallocation. Empirically, trading following posting tends to be short-term and does not result in large-scale changes to portfolio allocations. The pattern is consistent with a scenario in which investors process newly acquired information and make limited, short-horizon changes to test or incorporate those insights.

To assess whether trading offsets posting's performance bene fits, we examine their interaction in Table 12. The negative significant regression coefficient of the interaction term in initial months indicates that trading induces short-term frictions partially diluting posting gains, and the effect attenuates by t+2, suggesting that the costs are transitory (e.g., suboptimal timing or transaction fees). Crucially, posting's positive return effect remains persistently significant, whereas turnover's standalone effect fades. These findings imply that posting driven performance improvement stems not mechanically from trading activity, but from durable behavioural adjustments via social learning.

Taken together, our findings support the hypothesis (H1) that social interaction on the platform facilitates a form of adaptive learning. Investors acquire information through posting, process it through limited and temporally concentrated trading, and ultimately benefit from improved decision quality. The evidence is consistent with theoretical models of social learning in noisy environments, where individuals adjust incrementally in response to feedback and observation (e.g., Huang et al. 2021).

6.3 Heterogeneous Impact of Posting Types

Building on the evidence that trading serves as a vehicle for learning, we further examine whether the informational value of posting varies with the types of content shared. While previous evidence has shown that posting generally improves investment performance, such average effects may conceal important differences in how specific forms of communication influence decision-making. Our focus is, not all postings carry the same informational weight, and the cognitive intent embedded in different post types may shape the extent to which learning occurs.

Table 9
The lasting impact of posting on return.

	$Return_{t+1,t+n}$							
Variable name	$T+1$ **(1)**	$T+1$ **(2)**	$T+1\,T+2$ **(3)**	$T+1\,T+2$ **(4)**	$T+1\,T+3$ **(5)**	$T+1\,T+3$ **(6)**	$T+1\,T+6$ **(7)**	$T+1\,T+6$ **(8)**
Total Number of Posts	0.073**		0.079***		0.055***		0.038***	
	(0.029)		(0.020)		(0.016)		(0.010)	
Total Characters of Posts		0.026**		0.028**		0.018***		0.011***
		(0.012)		(0.008)		(0.007)		(0.004)
Constant	YES	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES	YES	YES
Observation	263,200	263,200	250,760	250,760	238,468	238,468	202,400	202,400
R-squared	0.001	0.001	0.009	0.009	0.010	0.010	0.018	0.018

Note: Standard errors are clustered at the investor level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
This table presents the results of the persistent effect of posting on return, $Return_{t+1,t+n}$ is the average of return of investor i from month $t+1$ to $t+n$, other settings are consistent with Table 4.

Table 10
Robust test of the lasting impact of posting on return.

Panel A. The lasting impact of posting on absolutely return

	Absolute return			
Variable name	$T+1$ **(1)**	$T+1\,T+2$ **(2)**	$T+1\,T+3$ **(3)**	$T+1\,T+6$ **(4)**
Total Number of Posts	95.631**	129.144***	180.079**	153.050**
	(38.150)	(44.821)	(90.372)	(72.676)
Constant	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES
Observation	264,385	253,011	241,604	207,372
R-squared	0.001	0.002	0.002	0.002

Panel B. Cross-sectional regression: the impact of posting on the alpha

	Alpha			
Variable name	**(1)**	**(2)**	**(3)**	**(4)**
Total Number of Posts	0.023**	0.021**		
	(0.010)	(0.010)		
Total Characters of Posts			0.025***	0.021**
			(0.009)	(0.009)
Control variables	NO	YES	NO	YES
Constant	YES	YES	YES	YES
Observation	11,715	11,715	11,715	11,715
R-squared	0.000	0.004	0.000	0.004

Note: Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Panel A presents fixed-effects panel regressions examining the effect of posting on cumulative absolute returns over various future horizons: 1, 2, 3, and 6 months. Other settings are consistent with Table 4.
Panel B reports results from cross-sectional regressions of investor-level alpha (estimated as the intercept from time-series regressions of monthly returns on market returns) on posting activity. $Alpha_i = \alpha + \beta_1 \quad Posting_{i,t} + x_i'\beta + \epsilon_i$

Table 11
The lasting impact of posting on turnover.

	$Turnover_{t+1,t+n}$		
Variable name	$T+1\,T+2$ **(1)**	$T+1\,T+3$ **(2)**	$T+1\,T+6$ **(3)**
Total Number of Posts	0.009***	0.005*	−0.004
	(0.003)	(0.003)	(0.003)
Control variables	YES	YES	YES
Constant	YES	YES	YES
Investor fixed effects	YES	YES	YES
Year-month fixed effects	YES	YES	YES
Observation	251,082	239,227	204,386
R-squared	0.013	0.005	0.003

Note: Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
This table presents the results of the persistent effect of posting on turnover, $Turnover_{i,t+1,t+n}$ is the logarithm of the average of turnover rate of investor i from month $t+1$ to $t+n$, other settings are consistent with Table 4.

Table 12
The results of the moderating effect of trading in posting on return over a period of time.

	Return							
Variable name	$T+1$ **(1)**	$T+1$ **(2)**	$T+1\,T+2$ **(3)**	$T+1\,T+2$ **(4)**	$T+1\,T+3$ **(5)**	$T+1\,T+3$ **(6)**	$T+1\,T+6$ **(7)**	$T+1\,T+6$ **(8)**
Total Number of Posts	0.050*		0.054***		0.038**		0.030**	
	(0.029)		(0.020)		(0.016)		(0.011)	
Total Characters of Posts		0.026**		0.029***		0.019***		0.010**
		(0.012)		(0.009)		(0.007)		(0.004)
Turnover	−0.165***	−0.164***	−0.030	−0.022	−0.006	−0.004	−0.005	−0.005
	(0.028)	(0.029)	(0.027)	(0.027)	(0.028)	(0.028)	(0.027)	(0.027)
Total Number of Posts Turnover*	−0.063***		−0.078***		−0.013		−0.008	
	(0.016)		(0.016)		(0.015)		(0.018)	
Total Characters of Posts Turnover*		−0.032***		−0.044***		−0.008		−0.001
		(0.009)		(0.009)		(0.008)		(0.010)
Constant	YES	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES	YES	YES
Observation	263,200	263,200	250,760	250,760	238,468	238,468	202,400	202,400
R-squared	0.002	0.002	0.011	0.010	0.011	0.011	0.019	0.019

Note: Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
This table reports the result of the moderating effect of trading in posting on return over a period of time (within 6 months) and estimate the following equation, $Return_{i,t+1,t+n}$ is the average of return of investor i from month $t+1$ to $t+n$, other settings are consistent with Table 4.
$Return_{i,t+1,t+n} = \beta_0 + \beta_1 \ \ Posting_{i,t} + \beta_2 \ \ Trading_{i,t} + \beta_3 \ \ Posting_{i,t}{}^{*}Trading_{i,t} + \beta' x_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$

Table 13
The impact of different types of posting on trading behaviour.

Panel A. The impact of different types of posting on the number of trading

	Total number of trades				Number of fund purchase				Number of fund redemption			
Variable name	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Number of Opinions Posted	0.141***				0.144***				0.109***			
	(0.005)				(0.005)				(0.004)			
Number of Comments Posted		0.140***				0.142***				0.106***		
		(0.005)				(0.005)				(0.004)		
Number of Questions Posted			0.197***				0.195***				0.167***	
			(0.020)				(0.022)				(0.019)	
Number of Answers Posted				0.109***				0.111***				0.075***
				(0.024)				(0.025)				(0.020)
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observation	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385
R-squared	0.080	0.080	0.072	0.071	0.049	0.049	0.041	0.041	0.082	0.082	0.076	0.076

Panel B. The impact of different types of posting on the amount of trading

	Total amount of trades				Amount of fund purchase				Amount of fund redemption			
Variable name	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Number of Opinions Posted	0.227***				0.274***				0.316***			
	(0.011)				(0.012)				(0.014)			
Number of Comments Posted		0.222***				0.270***				0.315***		
		(0.011)				(0.012)				(0.014)		
Number of Questions Posted			0.302***				0.319***				0.509***	
			(0.042)				(0.050)				(0.072)	
Number of Answers Posted				0.098***				0.099**				0.156**
				(0.037)				(0.041)				(0.071)
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observation	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385	264,385
R-squared	0.098	0.098	0.096	0.096	0.052	0.052	0.048	0.048	0.086	0.086	0.083	0.083

Note: Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
This table reports the result of different types of posting on trading behaviour. The type of the posts includes *Opinions, Comments, Questions* and *Answers*. In Panel A, our dependent variable is the number of the trading. In Panel B, our dependent variable is the number of the trading. Other settings are consistent with Table 4.

Table 14
The impact of different types of posting on performance.

	Return			
Variable name	**(1)**	**(2)**	**(3)**	**(4)**
Number of Opinions Posted	0.049**			
	(0.025)			
Number of Comments Posted		0.007		
		(0.024)		
Number of Questions Posted			0.212***	
			(0.082)	
Number of Answers Posted				0.079
				(0.073)
Constant	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES
Observation	263200	263200	263200	263200
R-squared	0.001	0.001	0.001	0.001

Note: Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
This table reports the result of different types of posting on return. The type of the posts includes *Opinions, Comments, Questions* and *Answers*. Other settings are consistent with Table 4.

Specifically, as discussed in previous sections, we classify posts into four categories: opinions, comments, questions, and answers, to empirically test the heterogeneous impact of posts on trading, Table13 presents the results. We find that question posts are associated with the largest increase in trading activity across all specifications, followed by opinion posts. Comments and answers exhibit substantively weaker but persistently significant economic effects. These differences reflect the varying informational functions of each post type: Questions are typically forward-looking and signal an explicit demand for clarification or insight, while opinions reflect the expression of personal beliefs that may invite feedback or challenge. Comments and answers, in contrast, are often reactive and anchored in existing content, which limits their role in generating new informational signals. These distinctions provide further empirical support for social learning, indicating that the effectiveness of social interaction depends not simply on participation, but on the informational intent.

We also observe a consistent pattern in the heterogeneous impact of posting on the investment performance. In Table 14, amongst the four post types, question posts are associated with the largest and most significant improvements in returns. Opinion posts also display a positive effect, but the magnitude is notably smaller. In contrast, the coefficients of comments and answers are not statistically significant. These findings reinforce the view that the impact of posting on investment outcomes is shaped by the nature of the content. When posting reflects an active search for clarification or the deliberate articulation of private beliefs, it is more likely to facilitate learning and lead to improved portfolio decisions (e.g., Huang et al. 2021). Passive or reactive forms of engagement, by contrast, appear less effective in generating useful informational feedback.

In summary, our findings provide further empirical support for the social learning channel. The cognitive orientation of posting, whether to seek clarification, to express a personal view, or to simply respond, plays a central role in shaping the impact of interaction on investment decisions. Posts that reflect active intent to acquire or structure information

are more likely to trigger feedback and lead to belief revision. In contrast, reactive content contributes less to learning. The heterogeneity across post types suggests that the effectiveness of social interaction depends not on volume alone, but on the informational purpose and depth embedded in the communication.

7 Further Discussion

7.1 Social Learning Across Position Adjustment

Building on the evidence that social interaction promotes investor learning, we examine whether the effectiveness of posting varies across investors with different portfolio compositions. We hypothesize that asset classes characterised by higher informational sensitivity or greater flexibility in interpretation may facilitate stronger learning effects. The empirical tests focus on three dimensions: the effect of posting on fund allocation, the moderating role of fund composition in the return - posting relationship, and performance heterogeneity across investor groups segmented by dominant fund type.[20]

First, Panel A of Table 15 reports the impact of posting on the allocation of different fund types. Investors who post more frequently tend to increase their holdings across all four categories—hybrid, index, stock, and bond funds. Second, we test whether the performance effect of posting depends on the composition of the investor's portfolio in Panel B. By interacting posting with the proportion of each fund type, we find that posting generates stronger performance for those with greater exposure to index and stock funds.[21] Third, Panel C provides further confirmation by categorising investors according to their dominant fund type. The regression results show that the positive association between posting and performance is strongest amongst investors whose portfolios are primarily composed of index funds.[22]

Overall, our findings show that social interaction's impact on investment performance depends on portfolio structure. Social learning's effect is not uniform; it is stronger in portfolios like index or stock funds, where investors face greater uncertainty and have more discretion for interpretation and adjustment. Conversely, for investors concentrated in hybrid or bond funds—characterised by more stable returns and narrower decision margins—the marginal value of informal information appears limited.

7.2 Individual-Level Heterogeneity in Social Learning

We then investigate whether the effect of posting on investment performance varies with investor characteristics. Table 16 reports the results, including gender (Panel A), age (Panel B), risk tolerance level (Panel C), asset (Panel D), and digital literacy (APP usage, Panel E).

Our results reveal significant heterogeneity across age, risk preferences, wealth level, and digital engagement. Younger investors benefit more from posting, while the effect is statistically insignificant for those aged 40 and above. Similarly, only investors with high risk tolerance exhibit significant return gains, suggesting that more conservative investors may be less inclined to act on socially acquired signals. The impact is also concentrated amongst lower-asset investors, consistent with the idea that less wealthy individuals rely more heavily on external sources of information. Finally, digital literacy—proxied by cumulative app usage—is strongly correlated with learning effectiveness: those with higher digital engagement show significantly stronger return responses to posting.[23]

Table 15
The impact of posting on fund allocation.

Panel A. The impact of posting on fund allocation

Variable name	Proportion of hybrid fund (1)	Proportion of index fund (2)	Proportion of stock fund (3)	Proportion of bond fund (4)
Total Numbers of Posts	1.571***	1.342***	0.213***	0.195***
	(0.194)	(0.164)	(0.081)	(0.072)
Constant	YES	YES	YES	YES
Control variable	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES
Observation	147,143	11,326	99,406	5325
R-squared	0.001	0.004	0.003	0.006

Panel B. The moderating effect of posting and fund type on performance

	Return			
Variable name	**(1)**	**(2)**	**(3)**	**(4)**
Total Number of Posts	0.126***	0.062***	0.121***	0.086***
	(0.048)	(0.022)	(0.033)	(0.030)
Proportion of hybrid fund	−0.000			
	(0.001)			
*Total Number of Posts*Proportion of hybrid fund*	−0.001			
	(0.001)			
Proportion of index fund		0.006***		
		(0.001)		
*Total Numbers of Posts*Proportion of index fund*		0.004***		
		(0.001)		
Proportion of stock fund			0.001	
			(0.001)	
*Total Number of Posts*Proportion of stock fund*			0.005***	
			(0.002)	
Proportion of bond fund				0.013***
				(0.001)
*Total Number of Posts*Proportion of bond fund*				0.002
				(0.001)
Constant	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES
Observation	262,141	262,141	262,141	262,141
R-squared	0.001	0.003	0.003	0.001

Panel C. The impact of posting on return of different investors

Variable name	Return			
Investor type	**Dominated by hybrid fund (1)**	**Dominated by index fund (2)**	**Dominated by stock fund (3)**	**Dominated by bond fund (4)**
Total Numbers of Posts	0.058	0.196*	0.098**	0.017
	(0.037)	(0.105)	(0.048)	(0.183)

(Continues)

Panel C. The impact of posting on return of different investors

Variable name	Return			
Investor type	Dominated by hybrid fund (1)	Dominated by index fund (2)	Dominated by stock fund (3)	Dominated by bond fund (4)
Constant	YES	YES	YES	YES
Control variable	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES
Year-month fixed effects	YES	YES	YES	YES
Observation	147,143	11,326	99,406	5325
R-squared	0.001	0.004	0.003	0.006

Note: Standard errors are clustered at the investor level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Panel A presents the impact of posting on fund allocation, we also control AR(1) term of *Proportion of hybrid fund*, *Proportion of index fund*, *Proportion of stock fund*, *Proportion of bond fund* in regression, respectively. Other settings are consistent with Table 4.
$Fund\ type_{i,t+1} = \beta_0 + \beta_1 \quad Posting_{i,t} + \beta' x_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$.
Panel B shows the result of the moderating effect of posting and fund type on investment performance, $Fund\ type_{i,t}$ including *Proportion of hybrid fund*, *Proportion of index fund*, *Proportion of stock fund*, *Proportion of bond fund*, other settings are consistent with Table 4.
$Return_{i,t+1} = \beta_0 + \beta_1 \quad Posting_{i,t} + \beta_2 \quad Fund\ type_{i,t} + \beta_3 \quad Posting_{i,t}{*}Fund\ type_{i,t} + \beta' x_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$.
Panel C reports the result of posting on different investors' performance. Based on the dominated fund type, we divide investors to four types: hybrid fund investor, index fund investor, stock fund investor, bond fund investor. Other settings are consistent with Table 4.

Table 16
Heterogeneity of social learning by trading.

Panel A. Heterogeneity of gender

	Return					
	Male			Female		
Variable name	(1)	(2)	(3)	(4)	(5)	(6)
Total Number of Posts	0.064*		0.045	0.087*		0.048
	(0.034)		(0.034)	(0.050)		(0.050)
Turnover		−0.195***	−0.146***		−0.300***	−0.234***
		(0.029)	(0.033)		(0.052)	(0.053)
Total Number of Posts Turnover*			−0.054***			−0.110***
			(0.018)			(0.035)
Constant	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES
Observation	185,401	185,401	185,401	77,799	77,799	77,799
R-squared	0.001	0.002	0.002	0.001	0.002	0.003

Panel B. Heterogeneity of age

	Return					
	Age < 40			Age ≥ 40		
Variable name	(1)	(2)	(3)	(4)	(5)	(6)
Total Number of Posts	0.098***		0.081**	0.033		0.002
	(0.037)		(0.038)	(0.044)		(0.044)
Turnover		−0.201***	−0.163***		−0.244***	−0.173***
		(0.033)	(0.038)		(0.038)	(0.041)

(Continues)

Panel B. Heterogeneity of age

	Return					
	Age < 40			Age ≥ 40		
Variable name	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Total Number of Posts Turnover*			−0.042**			−0.095***
			(0.021)			(0.026)
Constant	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES
Observation	152,184	152,184	152,184	111,016	111,016	111,016
R-squared	0.002	0.002	0.002	0.001	0.002	0.002

Panel C. Heterogeneity of risk tolerance level

	Return					
	Risk tolerance level ≥ 4			Risk tolerance level < 4		
Variable name	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Total Number of Posts	0.110***		0.090***	0.037		0.012
	(0.040)		(0.040)	(0.041)		(0.041)
Turnover		−0.215***	−0.158***		−0.218***	−0.170***
		(0.034)	(0.039)		(0.035)	(0.039)
Total Number of Posts Turnover*			−0.060***			−0.065***
			(0.022)			(0.024)
Constant	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES
Year-,onth FE	YES	YES	YES	YES	YES	YES
Observation	124,651	124,651	124,651	138,5-49	138,549	138,549
R-squared	0.001	0.002	0.002	0.001	0.002	0.002

Panel D. Heterogeneity of asset

	Return					
	Asset < 100,000 Yuan			Asset ≥ 100,000 Yuan		
Variable name	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Total Number of Posts	0.108***		0.085**	0.037		0.020
	(0.041)		(0.041)	(0.040)		(0.040)
Turnover		−0.194***	−0.157***		−0.159***	−0.491***
		(0.030)	(0.033)		(0.057)	(0.062)
Total Number of Posts Turnover*			−0.053***			−0.021
			(0.020)			(0.0332)
Constant	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES

(Continues)

Panel D. Heterogeneity of asset						
	Return					
	Asset < 100,000 Yuan			Asset ≥ 100,000 Yuan		
Variable name	(1)	(2)	(3)	(4)	(5)	(6)
Observation	152,927	152,927	152,927	109,214	109,214	109,214
R-squared	0.001	0.003	0.003	0.001	0.004	0.004
Panel E. Heterogeneity of APP usage						
	Return					
	APP Usage ≥ 8 years			APP Usage < 8 years		
Variable name	(1)	(2)	(3)	(4)	(5)	(6)
Total Number of Posts	0.098**		0.070*	0.043		0.026
	(0.039)		(0.039)	(0.042)		(0.042)
Turnover		−0.268***	−0.196***		−0.174***	−0.137***
		(0.041)	(0.048)		(0.031)	(0.034)
Total Number of Posts Turnover*			−0.085***			−0.045**
			(0.025)			(0.022)
Constant	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Investor fixed effects	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES
Observation	128,343	128,343	128,343	134,857	134,857	134,857
R-squared	0.001	0.002	0.002	0.002	0.002	0.002

Note: Online Table 1 reports the results of the heterogeneity of learning from posting based on various investor characteristics, including gender (Panel A), age (Panel B), risk tolerance level (Panel C), asset (Panel D), and digital literacy (APP usage, Panel E). Other settings are consistent with Table 4. Standard errors are clustered at the investor level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Our findings suggest that social learning interacts with an investor's behavioural traits and informational capacity. Younger, risk-tolerant, and digitally literate investors appear more capable of absorbing feedback and adjusting beliefs through social interaction. In contrast, investors with greater experience, more conservative preferences, or weaker digital familiarity may be less responsive to informal signals. The effectiveness of posting as a learning mechanism thus depends not only on content but also on the investor's cognitive readiness and behavioural elasticity.

8 Conclusion

Posting on social platforms represents a complex form of social interaction amongst investors, driven by diverse motivations. Using unique data from the large-scale fintech platform of Ant Group, we investigate how investor participation in online communities through posting influences trading behaviour and investment returns. Our analysis shows that posting significantly boosts total fund trading, purchases, and redemptions. Furthermore, we find that trading plays a crucial role in social learning through posting. Our findings reveal that posting significantly enhances investment returns, with positive effects lasting for at least 6 months. Although trading incurs short-term losses, these costs diminish over time, aligning with the concept of learning costs. The combined impact of posting and trading transitions from a short-term negative effect to no long-term significance, highlighting an iterative learning process where investors refine their strategies, absorb feedback, and mitigate biases through continuous social interaction. Finally, we identify that young investors, those with high risk tolerance, low assets, and high digital literacy are particularly adept at social learning through these interactions.

Our findings suggest several policy implications for fintech platform design and governance: platforms can improve retail investor welfare by enabling informed participation, filtering low-quality signals, and aligning content with decision needs. Specifically, first, platforms can enhance content availability through verified posting, standardized retail-oriented performance summaries, and interpretable portfolio data formats. Second, they boost interaction credibility by algorithmically prioritizing analytically grounded discussions over sentiment-driven posts. Third, they can increase engagement relevance through customisable interfaces that align information access with users' risk profiles, investment styles, or asset preferences.

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Conflicts of Interest
The authors declare no conflicts of interest.

Data Availability Statement
The data that support the findings of this study are available from Ant Group. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from www.deor.org.cn with the permission of Ant Group.

Endnotes

[1] According to Goldstein et al. (2021), big data can appear in various forms, such as posts, text, images, videos, etc. In this paper, we focus on posts that investors can interact with on social media.
[2] Due to some privacy issues, the study is remotely conducted on the Ant Open Research Laboratory in an Ant Group Environment. All data was sampled and desensitized and was analyzed on the Ant Open Research Laboratory.
[3] To be specific, we find that investors who are male, young, holding fewer funds, having higher risk tolerance, and engaging in more trading are more inclined to post, indicating that irrational investors may account for most posts.
[4] We substitute the dependent variable with turnover for both the full sample and the 95% winsorized sample.

[5] If trading decreases investment returns, it raises concerns about social platforms' informational efficacy. Conversely, if platforms improve investment returns, trading may reflect short-term adjustments from social learning. We therefore examine the relationship between posting, trading, and returns, focusing on social learning's role in investment decisions.

[6] After investors post content on the platform, unless investors voluntarily delete or the post is considered as a violation of platform rules, it will be saved on the platform for a long period of time.

[7] The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis and individual observations are invisible.

[8] Although the data originate from a single Chinese platform, its structural features are broadly comparable to other social-financial applications. Platforms such as Eastmoney and Snowball in China, or Robinhood and eToro in the United States, similarly embed trading tools within interactive community settings. The mechanisms of user-generated content and socially driven trading studied here are not unique to one institutional context but reflect a growing global trend toward socially mediated investing.

[9] While we observe investment performance, trading behaviour and asset allocation, the data do not contain fund-level details such as specific fund holdings.

[10] Despite these constraints, the data allow for an empirical examination of how investor behaviour and platform-based social engagement jointly shape financial outcomes in a digital environment.

[11] Due to privacy protection measures, we do not have access to the detailed content of the posts made by investors.

[12] Since asking questions is a direct way to obtain information, investors can obtain new information from the answers of other users by asking questions in the post.

[13] Standard errors are clustered at the investor level in all panel models throughout the paper.

[14] While the use of lagged explanatory variables partially mitigates this concern, these issues need a more rigorous identification strategy.

[15] The treatment group is defined as investors who have posted on the platform, and the control group includes those who have never posted.

[16] |SMD| < 10% indicates no significant difference in both groups.

[17] To investigate the lasting impact of posting on investment behaviour and distinguish between long-term and short-term effects, we used the rolling average of investment behaviour. Specifically, we use the monthly averages of *return* and *turnover* in Section 6 for periods $t + 1$ to $t + n$ as the dependent variables. Therefore, $Return_{i,\ t+1,\ t+n}$ is the average of return of investor i from month $t + 1$ to $t + n$; $Turnover_{i,\ t+1,\ t+n}$, is the logarithm of the average of turnover rate of investor i from month $t + 1$ to $t + n$.

[18] We only have data at the investor account level. For each investor, we estimate a 24-month time-series regression of monthly returns on market returns. The intercept (*Alphai*) from this regression captures the investor's risk-adjusted performance, net of market exposure.

$$\mathrm{Ret}_{i,t} = Alpha_i + \beta_i Mktrf + \epsilon_{i,t}$$

[19] Table 11 presents the results of the persistent effect of posting on turnover, $Turnover_{t+1,\ t+n}$ is the logarithm of the average of turnover rate of investor i from month $t + 1$ to $t + n$.

[20] The main position refers to the fund type that accounts for the largest share of an investor's total holdings. While we do not observe fund-level identifiers, we do observe the aggregate position size across different fund categories.
[21] The interaction terms are statistically and economically significant for these two categories, whereas no such amplification is observed for hybrid or bond funds.
[22] Stock fund investors also exhibit significant but smaller return. In contrast, hybrid and bond fund investors show no statistically meaningful improvement in returns.
[23] Although both age and platform usage experience are relevant to capacity to benefit from social learning, they capture distinct dimensions. Age reflects cognitive adaptability and behavioural receptiveness, while App usage years proxy digital familiarity and operational experience.

References

Ali-Rind, A., S. Boubaker, and S. L. Jarjir. 2023. "Peer Effects in Financial Economics: A Literature Survey." *Research in International Business and Finance* 64: 101873.

Ammann, M., and N. Schaub. 2021. "Do Individual Investors Trade on Investment-Related Internet Postings?" *Management Science* 67: 5679–5702.

Antweiler, W., and M. Z. Frank. 2004. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards." J*ournal of Finance* 59: 1259–1294.

Bala, V., and S. Goyal. 1998. "Learning From Neighbours." *Review of Economic Studies* 65: 595–621.

Barber, B. M., and T. Odean. 2000. "Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors." *Journal of Finance* 55: 773–806.

Barber, B. M., and T. Odean. 2002. "Online Investors: Do the Slow Die First?" *Review of Financial Studies* 15: 455–488.

Barber, B. M., and T. Odean, 2013, "Chapter 22 - The Behavior of Individual Investors." In *Handbook of the Economics of Finance*, edited by G. M. Constantinides, M. Harris, and R. M. Stulz, Elsevier.

Bartov, E., L. Faurel, and P. Mohanram. 2023. "The Role of Social Media in the Corporate Bond Market: Evidence From Twitter." *Management Science* 69, no. 9: 4973–5693.

Bartov, E., L. Faurel, and P. S. Mohanram. 2017. "Can Twitter Help Predict Firm-Level Earnings and Stock Returns?" *Accounting Review* 93: 25–57.

Blocher, J. 2016. "Network Externalities in Mutual Funds." *Journal of Financial Markets* 30: 1–26.

Bursztyn, L., F. Ederer, B. Ferman, and N. Yuchtman. 2014. "Understanding Mechanisms Underlying Peer Effects: Evidence From a Field Experiment on Financial Decisions." *Econometrica* 82: 1273–1301.

Cao, S., Z. Qiu, X. Shao, and K. Song. 2024. "Becoming an Opinion Leader in the Fintech Platform." Working Paper. Renmin University of China.

Chang, E. C., W. C. Joseph, and A. Khorana. 2000. "An Examination of Herd Behavior in Equity Markets: An International Perspective." *Journal of Banking & Finance* 24: 1651–1679.

Chen, H., P. De, Y. Hu, and B. H. Hwang. 2014. "Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media." *Review of Financial Studies* 27: 1367–1403.

Crawford, S. S., W. R. Gray, and A. E. Kern. 2017. "Why Do Fund Managers Identify and Share Profitable Ideas?" *Journal of Financial and Quantitative Analysis* 52: 1903–1926.

Das, S. R., and M. Y. Chen. 2007. “Yahoo! for Amazon: Sentiment Extraction From Small Talk on the Web.” *Management Science* 53: 1375–1388.
De Giorgi, G., and M. Pellizzari. 2014. “Understanding Social Interactions: Evidence From the Classroom.” *Economic Journal* 124: 917–953.
De Giorgi, G., M. Pellizzari, and S. Redaelli. 2010. “Identification of Social Interactions Through Partially Overlapping Peer Groups.” *American Economic Journal: Applied Economics* 2: 241–275.
Einav, L., and J. Levin. 2014. “Economics in the Age of Big Data.” Science 346: 1243089.
Farrell, M., T. C. Green, R. Jame, and S. Markov. 2022. “The Democratization of Investment Research and the Informativeness of Retail Investor Trading.” *Journal of Financial Economics* 145: 616–641.
Frydman, C. 2015. “What Drives Peer Effects in Financial Decision Making? Neural and Behavioral Evidence.” Working Paper.
Goldstein, I., C. S. Spatt, and M. Ye. 2021. “Big Data in Finance.” *Review of Financial Studies* 34: 3213–3225.
Gong, Q., M. Ban, Y. Yu, L. Wang, and Y. Yuan. 2023. “Digital Wealth Management and Consumption: Micro Evidence From Individual Investments.” *China Economic Review* 81: 102022.
Han, B., and L. Yang. 2013. “Social Networks, Information Acquisition, and Asset Prices.” *Management Science* 59: 1444–1457.
Heimer, R. Z. 2016. “Peer Pressure: Social Interaction and the Disposition Effect.” *Review of Financial Studies* 29: 3177–3209.
Heimer, R., and A. Simsek. 2019. “Should Retail Investors' Leverage Be Limited?” *Journal of Financial Economics* 132: 1–21.
Hirschey, M., V. J. Richardson, and S. Scholz. 2001. “Value Relevance of Nonfinancial Information: The Case of Patent Data.” *Review of Quantitative Finance and Accounting* 17: 223–235.
Hong, H., J. D. Kubik, and J. C. Stein. 2005. “Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers.” *Journal of Finance* 60: 2801–2824.
Huang, S., B. H. Hwang, and D. Lou. 2021. “The Rate of Communication.” *Journal of Financial Economics* 141: 533–550.
Kaustia, M., and S. Knüpfer. 2012. “Peer Performance and Stock Market Entry.” *Journal of Financial Economics* 104: 321–338.
Kim, S.-H., and D. Kim. 2014. “Investor Sentiment From Internet Message Postings and the Predictability of Stock Returns.” *Journal of Economic Behavior & Organization* 107: 708–729.
Odean, T. 1999. “Do Investors Trade Too Much?” *American Economic Review* 89: 1279–1298.
Pedersen, L. H. 2022. “Game On: Social Networks and Markets.” *Journal of Financial Economics* 146: 1097–1119.
Stein, J. C. 2008. “Conversations Among Competitors.” *American Economic Review* 98: 2150–2162.
Tumarkin, R., and R. F. Whitelaw. 2001. “News Or Noise? Internet Postings and Stock Prices.” *Financial Analysts Journal* 57: 41–51.

Wang, H., F. Yu, T. Reardon, J. Huang, and S. Rozelle. 2013. “Social Learning and Parameter Uncertainty in Irreversible Investments: Evidence From Greenhouse Adoption in Northern China.” *China Economic Review* 27: 104–120.
Wang, Y., P. Leon, K. Scott, X. Chen, A. Acquisti, and L. Cranor, 2013, Privacy Nudges for Social Media: An Exploratory Facebook Study, (ACM).
Wermers, R. 1999. “Mutual Fund Herding and the Impact on Stock Prices.” *Journal of Finance* 54: 581–622.
Zhang, A., P. Ni, and C. Ling. 2022. “Peer Effects in Rural Housing Demand: Evidence From China.” *China Economic Review* 73: 101787.