Digital Transmission of Financial Knowledge: Evidence from Stock Market Investment*

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Abstract

We study digital platforms' transmission of financial knowledge and their effects on users' investment in stocks and performance. Leveraging a proprietary dataset from one of China's largest digital platforms, we measure users' acquisition of financial knowledge through various platform information channels. Using a quasi-experiment setting to instrumentalize the acquisition, we find that the acquisition substantially increases stock market participation and enhances investment behaviors' sophistication and performance, especially for older, inexperienced, and less wealthy households. Thus, digitalization democratizes finance by providing low-cost and scalable financial education, empowering individuals to make investment decisions aligned with portfolio theory.

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1 Introduction

The rapid advancement of digitalization has profoundly transformed the financial services industry, encompassing investment (D'Acunto et al., 2019; Reher and Sokolinski, 2024), saving (Gargano and Rossi, 2024), lending (Buchak et al., 2018; D'Acunto et al., 2022), and payment services (Dubey and Purnanandam, 2023; Higgins, 2020). This transformation has expanded financial inclusion by reducing transaction costs (Agarwal et al., 2020; Vissing-Jørgensen, 2002) and enabling unbanked individuals to access financial services (Babina et al., 2024; He et al., 2023). Robo-advisory services have proven particularly beneficial for less wealthy investors (Reher and Sokolinski, 2024) as well as those with under-diversified portfolios (D'Acunto et al., 2019). Hvide et al. (2024) show that increased internet use promotes a "democratization of finance" (Shiller, 2007) by boosting stock market participation and enhancing financial decision-making among individual investors.

However, the impact of digitalization on households is not entirely positive. Although digitalization brings new opportunities for financial services, it also exacerbates behavioral biases in users, especially those with limited financial knowledge. Research by Barber et al. (2022) reveals that the fintech brokerage Robinhood attracts relatively inexperienced investors and its easy-to-use app induces the trading of high-attention stocks. Furthermore, social media usage appears to have positive and negative effects on the quality of financial decisions (Allen et al., 2021; Hirshleifer et al., 2023). While digital credit addresses customers' liquidity needs, many borrowers are unaware of loan terms, resulting in late repayments and significant fees (Brailovskaya et al., 2024). According to Prete (2022), assessing the implications of digitalization for investors should consider financial literacy, as individuals can access digital financial services even without being financially literate. This is a concern, given that only 33 percent of adults worldwide are financially literate, based on the S&P Global FinLit Survey.

Integrating diverse financial information channels into digital platforms can empower

users to acquire financial knowledge and mitigate behavioral biases. These online investment platforms facilitate connections between financial institutions, asset managers, and clients. They can offer updated financial education on a large scale at low costs. Additionally, they allow for the simultaneous acquisition of essential knowledge and practical information on financial instruments. This approach is scalable and cost-effective, with unrestricted access across different user characteristics, time, and location, compared to traditional financial education programs (Kaiser et al., 2022). Still, the study on the impact of digital transmission of financial knowledge on individuals' financial decisions and investment performance is sparse.

This paper's research question is whether and how digital transmission of financial literacy on a digital platform leads mostly uninitiated households to participate meaningfully in the stock market. Our research question is essential in household finance since households benefit from financial markets only if they participate and hold well-diversified investment portfolios (Campbell, 2006). However, low stock market participation still exists even in many advanced countries (Haliassos and Bertaut, 1995; Panizza, 2015).

China provides an interesting context for our study. In 2022, approximately 14% of the Chinese population (around 200 million individuals) invest directly in the stock market, [1] holding 20% of the total shares (Jones et al., 2023; Tan et al., 2024). Furthermore, retail investors in China, particularly those with smaller account sizes, are characterized by speculative trading behaviors that prioritize short-term gains and attention-grabbing stocks and exhibit many behavioral biases (Jones et al., 2023). The general population's participation rate is lower among middle- and lower-income households. Equity investment represents only a small fraction of total household assets (less than 2%).[2] The 2019 survey data show that Chinese households tend to concentrate their wealth in real

[1] The statistics are sourced from Chairman Yi Huiman's keynote speech at the 2022 Financial Street Forum Annual Conference.

[2] According to "Survey on the Assets and Liabilities of Urban Households in China in 2019", financial assets constitute only 20% of total household assets, and equities combined with funds make up just 10% of financial assets. Given the relatively low proportion of equity-based funds, stocks account for less than 2% of urban households' total assets.

estate (59.1%) and financial assets (20.4%), such as bank deposits and wealth management products, many of which are linked to loans or local government debt rather than equities. (The rest are in the form of consumer durables and operating assets.)[3] Although equity-based wealth management products are available, they typically require substantial minimum balance commitments and pose informational barriers for broader participation. Finally, wealthier households are far less constrained and often have personalized wealth management services.

Most of the population faces substantial barriers to stock market participation, especially those with low financial literacy, limited resources, and non-user friendly access to financial services. The emergence of digital financial platforms provides a transformative opportunity. These platforms have the potential to help break down barriers to participation through low-cost financial education and user-friendly access to stock market investment. Such an approach holds great promise in many growing markets with similar challenges in enhancing financial literacy and promoting broader market participation (Klapper et al., 2015; Lusardi and Mitchell, 2014).

The digital platform being studied is one of China's largest online investment platforms, catering to over 1 billion customers, including 711 million monthly active users at the end of June 2020, covering a vast geographic scope and financial statuses. The platform provides suitable observations to answer our research question. We focus on the platform's users' mutual fund participation; these funds include six types of mutual funds-equity, bond, hybrid, index, QDII, and gold. Figure 1 shows that the distribution of platform users investing in these mutual funds. Panel A shows that as of December 2022, only approximately 5% of platform users maintained a balance exceeding 100 RMB (roughly 14 USD), a meager threshold that underscores the limited investment engagement among users. The majority of platform users exhibited minimal engagement,

[3]The rest are in the form of consumer durables and operating assets. Consumer durables account for 7.6%, while operating assets, including equipment and commercial property, comprise 12.9% of the total. All statistics are sourced from the "Survey on the Assets and Liabilities of Urban Households in China in 2019," published in the journal of China Finance.

with 14% holding investments between 0 and 100 RMB and 81% not investing in mutual equity funds altogether. Panels B to D provide additional insights, highlighting that non-investors in mutual funds are disproportionately represented by older individuals, less educated (no college degree), and less wealthy (with less than 50,000 RMB investible assets). These patterns reveal significant disparities in financial engagement in equity markets across demographic and socioeconomic groups. Individuals in these groups are more likely to lack financial literacy and investment capacity, which makes them particularly vulnerable to the risks associated with equities. It is useful to investigate the role of digital financial education in bridging these gaps.

The platform offers a personalized robo-advisor (PRA), and a wealth community (with a wealth forum inside) as its primary channels for disseminating financial knowledge. The PRA, based on AI technology, provides users with personalized investment advice and information. At the same time, the wealth community connects them with financial institutions, asset managers and economic experts to obtain up-to-date financial information and services. Inside the wealth community are a wealth forum and various other financial information channels, such as the super-topic section and columns authored by investment advisors and financial influencers. The wealth forum enables users to exchange personal opinions about various topics related to financial markets and investment products, while the super topic section provides the most updated financial issues and market trends. In the wealth community, all financial content presented as short videos or image-text is categorized as "Visual Content." The study utilizes users' access and exposure to these AI - digital information transmission channels to capture users' acquisition of financial knowledge through the platform, which we refer to as *Platform Exposure* subsequently.

Additionally, we obtain variables from the platform to measure a user's investment decisions from various perspectives, such as investing in equity-based mutual funds, portfolio's equity holding ratio, allocation score, automatic investment score, fund number,

fund type, fund balance and fund holding duration.[4] These detailed measures allow us to investigate the influence of the access and exposure to AI-digital information transmission channels via the platform on households' detailed investment behaviors, the study of which has been sparse in previous research in financial education programs.

We take advantage of the platform's marketing campaign, called "Wealth Festival," to promote its information services to mitigate the endogenous relation between the usage of the services and investment behavior. The campaign runs on the 18^{th} of each month and randomly distributes campaign messages to draw the participants' attention to the platform's digital information services. The randomized promotion allows us to overcome the identification challenge using a quasi-experimental campaign in January 2023. Our experimental population comprises the platform's monthly active users (those who have ever logged in to the platform from Dec 18^{th}, 2022 to Jan 18^{th}, 2023, the month right before the campaign) at least 18 years old with a valid risk level and who have never been alert of and used digital financial services before the January campaign (i.e., their platform exposure is zero from the beginning of 2021, the starting point of our data range, to Jan 18^{th}, 2023). The population is about 0.8 million. Some in this population received the randomly distributed digital campaign messages on Jan 18^{th}, 2023. Figure 2 displays the timeline for the January campaign. We set up a dummy, *Promotion*, to indicate whether a platform participant has received the marketing messages, and we use *Promotion* as an instrumental variable in our analysis. The platform exposure (gained during the campaign) instrumented by this IV is the explanatory variable in our baseline model.

We provide empirical evidence of the instrument's relevance. During the treatment period (January 2023), among 100,159 users who received the service promotion, 1,541 (1.5%) acquired platform exposure. In sharp contrast, within the control group, among 100,159 users who have never been service-promoted, only 59 (0.06%) acquired platform

[4]The detailed definition and calculation for these investment outcomes are shown in Table 1 and Appendix A1.

exposure. We also find that the treated and the control groups have a similiar distribution of demographic characteristics and of pre-treatment investment, which adds credence to the randomness in distributing the marketing campaign message to our sample population. Because users who received promotion before are much fewer than users who never service-promoted (around 0.68 million) during the marketing campaign, we use Coarsened Exact Matching (CEM) to strictly match user characteristics between the treated and non-treated users to to mitigate endogeneity further. Our final sample comprises 90,093 users from the treated and the same number from the control group.

We measure indirect stock market participation using *D(Stock Market Participation)*$_i$, which equals 1 if user i has ever purchased stock-type funds[5] through the platform during the campaign (Jan 18^{th}-Feb 17^{th}, i.e., the treatment month), and zero otherwise. We find that the digital platform exposure gained during the treatment month is significantly positively associated with stock market participation for those who have not participated in the stock market before the treatment (Dec 18^{th}, 2022 to Jan 17^{th}, 2023). Specifically, a unit increase in platform exposure corresponds to a 5.7% increase in the likelihood of stock market participation. Within the full range of platform exposure (0 to 100), this effect could translate into a potential increase of up to 570% in stock market participation likelihood. This effect is particularly noteworthy given that only 0.3% of the overall sample had participated in the stock market before the treatment. The economic significance of this impact underscores the potential of digital financial education in overcoming barriers to investing in the stock market, especially in populations with historically low participation rates. Moreover, on average, the platform exposure is also associated with a notable rise in users' equity holding ratio (the share of the stock-type funds in the portfolio) compared with the ratio before the treatment.

We also investigate whether the platform exposure gained during the promotion

[5]The platform offers six types of mutual funds-equity, bond, hybrid, index, QDII, and gold. Equity-based mutual funds include equity funds, hybrid funds, equity-based QDII and equity-based index mutual funds.

campaign is associated with improving investment behaviors and performance during the treatment month. We gauge investors' financial behaviors by six key indicators: *Fund Balance, Fund Number, Fund Type, Fund Holding Duration, Allocation Score*, and *Automatic Investment Score*. All these outcomes are measured by the average level change from the month before the January treatment to the treatment month ($\bar{Y}_{Jan18^{th}-Feb17^{th},2023} - \bar{Y}_{Dec18^{th},2022-Jan17^{th},2023}$). Our results reveal that the platform exposure gained during the treatment period significantly positively affects all measures of investment behavior. For instance, an increase in the platform exposure leads to an average increase in the mutual fund balance by 392 RMB (54 USD) with a longer holding duration. Based on the platform exposure range of [0, 100], the potential impact on fund balances is substantial, with an increase of up to RMB 39,200 (approximately USD 5,400), compared to a negligible average fund balance of RMB 0.01 prior to the treatment. Moreover, each unit increase in platform exposure can result in an increase in the number of funds held and the variety of fund types by 0.25 and 0.05, respectively. Considering the pre-treatment averages of 0.03 funds and 0.01 fund types, these improvements reflect significant growth, highlighting the role of platform exposure in enhancing portfolio diversification. Additionally, platform exposure contributes to improved portfolio allocation and automatic investment scores, with gains of 22.852 and 0.336 points, respectively. Relative to baseline averages, these changes represent a 9.18-fold increase in portfolio allocation capabilities and an 11.20-fold rise in the adoption of automatic investment strategies, which helps promote long-term financial growth through cost averaging. Altogether, these results validate that learning through the platform's digital information tools can improve investors' investment behaviors.

Turning to investment performance, we analyze the near-term effects: the impact of the platform exposure on portfolio returns during our treatment month relative to the month before treatment. Following Rossi and Utkus (2020), we measure performance as the annualized abnormal Sharpe Ratio, which is an investor's realized Sharpe ratio minus that of the market portfolio. We use the Shanghai Stock Exchange composite index as the

market portfolio. For each investor, portfolio returns are annualized using daily portfolio returns, and portfolio volatilities are computed as realized volatilities using squared daily returns. We find that the average improvement of the abnormal Sharpe ratio from the month before the treatment to the treatment month is significantly greater for the treated than for the control groups. The results show that the platform exposure significantly improves the risk-adjusted return during the treatment month.

We examine the heterogeneous effects of the platform exposure on investment behavior, differentiating by age, education level, and investable asset levels. Our focus on these characteristics is driven by their significant correlations with stock market participation (e.g., Briggs et al., 2021; Bucher-Koenen et al., 2021; Christelis et al., 2010; Lusardi et al., 2010; Van Rooij et al., 2011). These traits not only reveal existing disparities in market engagement but also enhance our understanding of how digital financial education can effectively address these gaps.

We find that younger individuals with higher education levels and lower wealth are more likely to acquire financial information from the platform. However, the promotion efforts appear less effective in engaging wealthier individuals, likely due to their access to alternative wealth management resources, such as personal wealth managers.

We also find that the impact of platform exposure varies across demographic groups, reflecting its capacity to cater to diverse investor needs. For younger individuals, who are likely less experienced with risky investments, platform exposure significantly enhances their stock market participation, equity holdings, and the adoption of automatic investment plans. In contrast, more educated individuals, who generally already possess the capacity to invest, benefit from digital financial education through improvements in portfolio diversification, which in turn enhances their investment performance. Interestingly, we find that the digital dissemination of financial knowledge enables even the older, less educated, and less wealthy individuals to overcome barriers to stock market participation, increase mutual fund investment and diversification, and improve investment

performance. Yet, there is room for improvement. For instance, more educated individuals could benefit from greater support in increasing their investment engagement, while younger investors might require targeted strategies to enhance portfolio diversification. Further research is needed to delve deeper into the underlying mechanisms driving these outcomes and to identify more tailored approaches for different demographic segments.

This paper makes two contributions. First, we empirically show that digital financial education and robot advisory on platforms empower investors to overcome barriers to stock market participation and improve their investment behaviors and performance. This result is particularly important given the widespread lack of financial literacy globally. Second, we show that digital financial education and robot advisory particularly benefit older, less educated, and less wealthy individuals. These groups usually avoid investing in stocks because of their limited financial literacy, vulnerability to risk in stock markets, and constrained investment capacity. Thus, digital financial education could genuinely raise financial inclusion. Our findings hold significant promise for policymakers, education program designers, and investors alike.

The remainder of the paper is organized as follows. Section 2 offers an overview of relevant literature. Section 3 provides institutional background on the platform, data and methodology for measuring the platform exposure and identification. Section 4 explores the platform exposure's causal impact on households' stock market participation, investment behaviors and investment performance, as well as its heterogeneous impacts across investors' characteristics. Some robustness checks are reported in Section 5. Finally, the paper concludes in Section 6.

2 Related Literature

This study contributes to multiple strands of the economics and household finance literature. It is primarily related to the literature on how digitized data, connectivity, and service affect individuals' investment behaviors.

The advancement of IT technology and digital transformation has substantially raised unbanked individuals' access to financial services, including investment (Reher and Sokolinski, 2024; Rossi and Utkus, 2020), saving (Gargano and Rossi, 2024), lending (Buchak et al., 2018; D'Acunto et al., 2022), and payment services (Higgins, 2020). Digital payment has lowered transaction costs and eased borrowing constraints, increasing business sales and consumer consumption (Agarwal et al., 2020; Dubey et al., 2023).

Still, the household finance literature raises a "stock market participation (SMP) puzzle" (Campbell, 2016; Gomes et al., 2021; Guiso and Sodini, 2013; Haliassos and Bertaut, 1995): individual participation in equity markets is low. Campbell (2006) suggests this is a concern for households who can benefit from financial markets only if they participate and hold well-diversified investment portfolios. The literature has suggested several factors that constrain SMP, including personal wealth (Briggs et al., 2021), culture and peer effect (Guiso et al., 2006; Hong et al., 2004), computer ownership (Bogan, 2008; Hvide et al., 2024), cognitive ability (Christelis et al., 2010; Grinblatt et al., 2011), and financial literacy (Kimball and Shumway, 2010; Lusardi and Mitchell, 2014; Lusardi et al., 2017; Van Rooij et al., 2011).

The IT advancement helps. It is well known that equity-based mutual funds (i.e., funds with equity shares or ETFs as the underlying securities) facilitate ordinary households' access to equity investment. Digital platforms also facilitate low-cost information acquisition. Hvide et al. (2024) emphasize the role of information in increasing stock market participation through internet use. Furthermore, with the advancement in AI technology, robo-advising has become an option, leveraging digitized data to provide automated and personalized investment advice, which has been shown to enhance investment performance (D'Acunto et al., 2019; Reher and Sokolinski, 2024; Rossi and Utkus, 2020). Yet, Babina et al. (2024) argue that using open banking data for advice benefits everyone, but warns that using data for credit promotion may inadvertently make borrowers worse off.

Financial literacy is worthy of emphasis. Previous studies have shown that financial literacy can empower investors to effectively manage their savings (Jappelli and Padula, 2013), investments (Lusardi et al., 2017), debts (Lusardi and de Bassa Scheresberg, 2013; Lusardi and Tufano, 2015), and consumption (Hasler et al., 2018). Additionally, it significantly contributes to financial inclusion (Grohmann et al., 2018; Kiril, 2020) and wealth inequality (Lusardi et al., 2017). Yet, raising the general public's financial literacy, especially the older, less well educated, and less wealth groups, can be a formidable task.

Note that along with the rapid expansion of digitalization, individuals can access digital financial services even without being financially literate. However, Prete (2022) suggests that it could be dangerous to increase digitalized access to finance without financial literacy. Servon and Kaestner (2008) find that technological training, coupled with e-banking, makes financial literacy training more appealing to participants, particularly low- and moderate-income individuals.

Our work contributes to the above literature by systematically revealing how a digital platform that offers access to equity-based mutual funds helps overcome the household stock market participation puzzle and improve households' investment efficiency via its digital delivery of financial literacy. As described in the Introduction, for communication convenience, we call access and exposure to these digital transmissions of financial knowledge, investment product information, and services "Platform Exposure." The platform exposure plays a causal role in the rise in household equity investment and the performance of such investment. The identification is via an exogenous randomly prompted access to these features. Using this random access to instrumentalize the platform exposure, we show the positive causal impact of digitally spreading financial literacy on investment behavior and outcome.

3 Background, Platform Exposure, Variables, Treadted and Control Group

3.1 Background and our platform setting

China provides an ideal laboratory for studying the effects of financial learning through digital platforms on individual investment behaviors. First, China's online investment platforms have experienced substantial growth, thanks to a 2012 policy permitting technology-based platforms to distribute mutual funds independently.[6] According to China International Capital Corporation's asset management industry report, the market share of FinTech platforms in the total mutual fund indirect sales grew from 22% to 42% between 2016 and 2018. In the last quarter of 2022, Ant Financial (10.11%) and Tiantian (8.24%) were among the top three players in the indirect sales of mutual funds.[7]

Second, Chinese households have experienced remarkable growth in net wealth over the past two decades, with personal investable assets reaching 160 trillion RMB (around 23 trillion USD) in 2019. However, a significant portion of personal investable assets (58%) is held in cash and deposits. Only 5% of the platform's users (over 1 billion) participated in the stock markets by purchasing stock-type funds as of December 2022. It would be desirable to uncover efficient ways to induce them to invest sensibly in organized markets other than bank deposits or real estate.

Platforms can use digital means and AI to spread financial literacy to potential users, and facilitate and even guide their market participation. Our empirical objective is to identify the causal impact of access and exposure to these features (platform exposure) on individual investment behavior.

[6] In February 2012, the China Securities Regulatory Commission (CSRC) announced that fintech companies can distribute mutual funds independently from banks, brokers, and fund families.

[7] According to market analysis, China Merchants Bank (CMB), Ant Financial, and Tiantian are currently the top performer in the mutual fund indirect sale market. Ant Financial holds approximately 10.11% of the stock and hybrid public fund market, which is valued at 571.2 billion RMB - a slightly lower figure than CMB's 620.4 billion RMB. Moreover, Ant Financial's non-MMFs make up 14.42% of the market, with a total value of 1154.5 billion RMB. Tiantian, on the other hand, boasts a market share of 8.24% in the stock and hybrid public fund sector, worth 465.7 billion RMB, and 7.30% in non-MMFs, worth 584.5 billion RMB.

The empirical setting is built on a marketing campaign by one of China's largest online investment platforms. The platform caters to over 1 billion customers in 2021, irrespective of their financial status. Through multiple channels, it provides onboard investors free digital access to financial knowledge and product information services. A marketing campaign called "Wealth Festival" is launched on the 18^{th} of every month to promote these digital services. Notices in the form of pop-up messages and banners on the platform's main page are randomly distributed to the platform users. The setting offers a quasi-experimental framework that helps address the identification challenge of establishing a causal relationship between platform exposure and investment behavior and outcomes. (We will elaborate on the quasi-experiment in Section 4.1.) We focus on the January 2023 campaign (started on Jan 18^{th} 2023) and mark Jan 18^{th} to Feb 17^{th}, 2023, as the "treatment month;" we cannot expand beyond the treatment month due to data limitations.

3.2 Platform Exposure

The key explanatory variable we want to link with changes in investment behavior is platform exposure, which measures users' acquisition of financial knowledge through various information channels on the platform. Platform exposure is quantified by the total effective interactions with the platform's digitalized financial information services and is assessed along both intensive and extensive margins. The intensive margin is the total length of interactive times a user accesses the digitalized financial information services within a given month. The extensive margin is established through binary variables that indicate whether additional digital financial services have been used in a month. This dual approach allows for a comprehensive evaluation of how platform exposure influences changes in investment behavior, distinguishing between the depth and breadth of users' interactions with digital financial education.

The components of the platform exposure are as follows:

Personalized Robo-Advisor (PRA): The platform offers an Investment AI Assistant designed to assist investors in identifying appropriate financial products while simultaneously enhancing their financial literacy. This service is tailored to individual needs and allows free access without restrictions on time, location, wealth, or income levels. Unlike traditional advisory services, it does not require a subscription. Through this feature, users can explore a wide array of financial products, gain insights into market trends, and access comprehensive financial education content alongside tailored investment advisory services. Additionally, PRA assists users in tracking their investment portfolio and alerts them when they may be making imprudent investment choices, such as selling or purchasing risky assets during market downturns.

Wealth Community: The all-in-one wealth community built inside the wealth platform is an inclusive space for both users and financial institutions. This community provides users with access to financial knowledge and market information through various channels as below:

1) Wealth Forum: The forum is built inside the wealth community and offers diverse financial topics, encompassing specific investment products and indexes. If users seek to gain a deeper understanding of a particular product or index, they can visit the product's forum to raise real-time questions and share ideas and experiences specific to this product. This interactive environment enriches the financial knowledge base of the community and fosters learning through peer interactions and collaborative discussions.[8].

2) Visual Content: It represents the financial information posted as short videos or image-texts in the wealth community. For example, partner asset managers from fund companies and renowned economists active in financial media can directly engage with users. They deliver digital financial education through formats such as short videos, offering market news and insights to help users navigate investment challenges and mitigate common pitfalls.

[8]See, Brown et al., 2008; Guiso and Jappelli, 2005; Hayta, 2008

3) Other: The wealth community also features a variety of other financial information channels, including the super-topic section, columns, and blogs authored by professional investment advisors and financial influencers. The super-topic section highlights the most current and trending financial topics, providing users with real-time updates on financial news and in-depth analyses. These channels aim to enhance users' understanding of market dynamics, offering a diverse array of perspectives and expert insights that facilitate more informed investment decisions.

We measure platform exposure by the total amount of time (in seconds) users spend interacting with the Personalized Robo-Advisor (PRA) and in the wealth community. These values are then scaled to a range of 0 to 100 using the following equation:

$$Platform \quad Exposure_i = \frac{Total\ Times_i - min(Total\ Times_i)}{max(Total\ Times_i) - min(Total\ Times_i)} * 100 \qquad (1)$$

where i represents the sample individual; Total Time_i denotes the total amount of time user i spends with the PRA and in the wealth community (measured in seconds); max(Total Time_i) and min(Total Time_i) represent the maximum and minimum values of the total time spent across all users in the sample, respectively. However, if an individual has not used any digitalized financial services provided by the PRA and the community, we mark her $PlatformExposure_i$ as zero. We note that $PlatformExposure_i$ is a monthly measure. For simplicity, we omit the time (month-year) subscript.

For robustness checks, we also consider the total number of days users engaged with the primary digital financial information channels—specifically, the PRA, wealth community, forum, visual content, and super-topic section. This alternative digital platform exposure measure is frequency-of-engagement based and complements the time-based metrics.

3.3 Other Variables

Our empirical work also needs data on (i) users' characteristics, (ii) users' response to the marketing campaign in the treatment month and thus their usage (or non-usage) of the platform's digital financial services, and iii) the average change in their investment outcomes before and during the treatment month. Therefore, we extract three data sets from the platform between October 18^{th} 2022 and July 17^{th} 2023.

The first data set includes investors' characteristics variables. For each investor, we observe age, gender, education level, province and city of residence, and risk level, which is measured by investors' answers to the platform's regular risk survey and represents risk tolerance. It ranges from 0 to 5.

The second dataset measures the extent a user receives digital messages promoting the platform's "Personalized Robo-advisors (PRA)" and "Wealth Community." Our IV $Promotion_i$ equals 1 if the sum of days that user i receives promotion during the January campaign 2023 (Jan 18^{th}-Feb 17^{th}, 2023) is one or greater, 0 otherwise. The data also records the length of times each month an investor visits digital services provided by the PRA and the wealth community, including its three subcomponents: "Wealth Forum," "Visual Content," and "Other." As these subcomponents are integral to the wealth community, the campaign materials promoting the wealth community are also promoting these digital financial services.

The third dataset comprises monthly observations on investors' investment behaviors and performance. There are seven investment outcome variables. The first is indirect stock market participation, *D(Stock Market Participation)*, which equals to one if investors have held stock-type funds through the mutual fund market during the treatment month and zero otherwise. The other six investment outcome variables are *Fund Balance, Fund Number, Fund Type, Fund Holding Duration, Allocation Score*, and *Automatic Investment Score*; they measure investors' investment, portfolio diversification, allocation, and management. Allocation Score and Automatic investment score are computed by

the platform's investment team to assess investors' asset allocation capabilities and their level of participation in an automated investment plan. Appendix AI reports the detailed calculation for these two metrics. The Allocation Score is higher for investors with more diversified portfolios. The automatic investment plan allows users to systematically invest a fixed amount into their chosen funds at regular intervals, promoting disciplined and consistent investing. This plan is a key feature of the platform and is designed to simplify the investment process and reduce the impact of market timing. As users engage more actively with the plan—by increasing the number of enrolled funds—their Automatic Investment Score rises, reflecting greater involvement and commitment to systematic investing. For each investor, portfolio returns are annualized using daily portfolio returns, and portfolio volatilities are computed as realized volatilities using squared daily returns. The annualized portfolio returns and volatilities are winsorized at the 1st and the 99th percentiles.

3.4 The Population, the Treated, and Control Groups

Our quasi-empirical experiment is implemented on a data population extracted from the platform, comprising monthly active users (i.e., users who have logged into the platform Dec 18^{th} 2022-Jan 17^{th} 2023, one month before the January 2023 campaign) above 17 who have no prior platform exposure and also have not received service promotion before the beginning day of the treatment month (Jan 18^{th}-Feb 17^{th}, 2023); that is, their *Platform Exposure*$_i$ and *Promotion*$_i$ are all zero from Oct 2022 to Jan 17^{th}, 2023.

Some in the extracted population receive randomly distributed service promotion messages (i.e., pop-up messages and banners on the platform's main page) during the treatment month. They form our treated group; there are 100,159 of them. Due to the platform's data regulations, we can only exact a portion of the population as our potential control; we randomly select the same number of observations (100,159 users) to serve as our potential control group.

To further ensure that the treated and control groups have similar characteristics, we use Coarsened Exact Matching (CEM) to match strictly treated and non-treated users on different baseline characteristics - age, gender, education, risk tolerance, investable asset level (which is a dummy variable indicating that a user has at least 50 thousand RMB to invest), and on whether they have mutual fund investment experiences. The matched sample ends up with 180,186 users. Figure 3 shows the parallel trends before and after the treatment (October 18^{th} 2022 - July 17^{th} 2023) in all investment outcomes between the treated and control groups. [9]

3.5 Summary Statistics

Table 1 shows that the distribution of the demographic characteristics and previous investment behaviors of the treated (Panel A) and non-treated users (Panel B) before matching are similar. The comparisons are based on the 3-month average of the variables from October 18^{th}, 2022 to January 17^{th}, 2023. Panel B Col.1 displays the t-test scores for the equality of the means for the treated's and non-treated's demographic characteristics, investment behaviors, and risk-taking before the treatment. These t-statistics are insignificant at the 10% significance level, except for the variables *Fund Balance, Allocation Score*, and *Fund Number*. However, the distributions of these variables in the two groups are similar; except for the Allocation Score, the differences in the means between the two groups disappear once we discard outliers. To further ensure the same distribution of the two groups, we use Coarsened Exact Matching (CEM) to strictly match treated and non-treated households on different baseline characteristics-age, gender, education, risk tolerance, investable asset level, and mutual fund investment experiences.

After matching, the treated and non-treated users have similar demographic characteristics and investment outcomes before the treatment, as shown in Table 2. The mean difference for each variable is no more than 0.1. We also test the null of whether the means

[9] Our design has been implemented in numerous disciplines, including medicine and the social sciences (see, for instance, Duflo and Saez, 2003; Fowlie et al., 2018; West et al., 2008).

of the treated and control distribution differ. None of the t-statistics are significant at the 10% significance level. Finally, the matched sample covers 180,186 users.

Panel A shows that the average age of users in the treated and matched sample is 37 years old, with 57% being male. Only 12% possess a bachelor's degree or higher, which is in line with China's overall education level. The average mutual fund investment experience is 1.4 months. Regarding investable assets, only 5% of the users have investable assets of CN¥50,000 (around 6,824 USD) or more.

Panel B reports the distribution of the treated and the matched users' 3-month average level of investment behaviors from October 18^{th} 2022 to January 17^{th} 2023, three months before the treatment. The average user has a risk level of 0.87 with scale of [0,5]. The average fund balance is 0.01 RMB (almost zero), resulting from a mere 0.8% of users having ever invested in mutual funds during this period. Similarly, around 0.3% of users have invested in the stock market through purchasing stock-type funds, and the average equity holding ratio is 0.13%, aligning well with China's low proportion of engagement in riskier asset markets. In terms of portfolio diversity, the average number of funds held by users is 0.03, with an average of 0.01 distinct types of funds and a duration of 0.35 days. The average allocation score is 2.49, while the automatic investment score is 0.04. Both of these two scores are measured on a scale from 0 to 100. The above averages reveal that the treated and matched groups indeed barely invest in stock markets or stock-type funds.

4 The Effects of Platform Exposure

In this section, we first provide the details of our identification in the quasi-experimental research design and then report our main empirical results on the impact of the platform exposure on stock market participation and related investment behaviors.

4.1 Identification

It is tempting to run regression analyses to explain the difference in the respective changes in the treated's and control group's investment behaviors from the pre- to the post-treatment periods by the changes in their respective platform exposure. However, as mentioned in Section 3.2, endogeneity arises because there is likely synergy between seeking platform exposure and making financial decisions. Also, time-invariant user characteristics, such as age, gender, and education, might simultaneously drive individuals' investment choices and their inclination to use digital financial services to acquire financial knowledge. While user-fixed effects can absorb time-invariant unobservable characteristics, user preferences for platform exposure may be time-varying and account for both the decision to use digital financial services and the shifts in investing behavior.

We overcome these identification challenges by exploiting the platform's marketing campaign features. The marketing campaign randomly distributes materials users, whom we collate into the treated group, through pop-up messages and banners during the treatment period to encourage them to use the digital financial services on the platform. We use the dummy $Promotion_i$ as an instrument to predict $Platform\ Exposure_i$ in the treatment month (Section 3.3 reports $Promotion_i$ equal 1 if a user's sum of days exposed to the digital marketing materials during the treatment period (Jan 18^{th}–Feb 17^{th}, 2023) is 1 or greater). Note that our treated group comprises users whose *Platform Exposure* is zero before the campaign (before Jan 18^{th} 2023) and with a *Promotion* equal to one during the treatment month (Jan 18^{th}–Feb 17^{th}, 2023). Note also that our matched control group comprises users whose *Platform Exposure* is zero before the campaign and with a *Promotion* equal to zero during the treatment month.

Hence, our first-stage cross-sectional regressions are as follows:

$$Platform\ Exposure_i = \alpha_i + \theta \mathbb{1}\{Promotion\}_i + \varepsilon_i \tag{2}$$

$$\mathbb{1}\{Platform\ Exposure\}_i = \alpha + \theta \mathbb{1}\{Promotion\}_i + \varepsilon_i \tag{3}$$

where $PlatformExposure_i$ in Eq.2 is the intensive margins measure of digital financial services the user i used during the treatment on a scale ranging from 0 to 100; $\mathbb{1}\{PlatformExposure\}_i$ in Eq.3 is the extensive margins measure, a dummy variable equal to 1 if the user i has used digital financial services to acquire financial knowledge during the treatment and zero otherwise.

In the second stage, we use Equations (4) and (5) to obtain causal estimates of the impact on the changes in users' stock market participation and investment behaviors, using the predicted $\widehat{PlatformExposure}_i$ and $\mathbb{1}\{\widehat{PlatformExposure}\}_i$ respectively as the main predictor:

$$Y_i = \alpha + \beta \widehat{Platform\ Exposure}_i + \varepsilon_i \tag{4}$$

$$Y_i = \alpha + \beta \mathbb{1}\{\widehat{Platform\ Exposure}\}_i + \varepsilon_i \tag{5}$$

where Y_i represents the investment outcomes; $\widehat{Platform\ Exposure}_i$ or $\mathbb{1}\{\widehat{PlatformExposure}\}_i$ is the key instrumented regressor.

The parameter of interest is β, which measures the mean difference in investment outcomes after acquiring the platform exposure; that is after having access and exposure to the platform's digitally delivered financial knowledge and related financial markets and products information.

4.2 Empirical Results

4.2.1 First Stage

In the first stage, we measure the platform exposure in intensive and extensive margins and estimate how service promotion affects the likelihood of acquiring financial knowledge and how much financial knowledge is acquired.

Table 3 shows our first-stage regression results based on Equation (2) and (3). Columns (1) and (2) report the results regarding the platform exposure in intensive and extensive margins. Column (1) shows that service promotion can increase the intensity of the platform exposure on average by 0.03. In column (2), we find that the instrument IV service promotion coefficient θ identifies a 1.4% increase in the probability of an uninitiated user acquiring the platform exposure during the treatment period. The parameter θ is close to the mean difference in the platform exposure between the treated and control group by extensive and intensive margins, respectively. So we effectively use the mean difference in the platform exposure between two groups as our instrumentalised estimator ($\widehat{Platform\ Exposure_i}$) for the second stage regression. We also find that the Kleibergen-Paap F-stat associated with these first-stage regressions are very large, indicating that the dummy variable IV represents a strong instrument.

4.2.2 Second Stage: Stock Market Participation

We first analyze how the platform exposure affects users' stock market participation. The dependent variables are *D(Stock Market Participation)* and $\Delta EquityRatio$. *D(Stock Market Participation)* is a dummy variable, which equals to 1 if the user i has participated in the stock market through purchasing stock-type funds during the treatment month ($Jan18^{th} - Feb17^{th}$). $\Delta EquityRatio$ measures the monthly average change in the share of equity in the portfolio from the month before the treatment ($Dec18^{th} - Jan17^{th}$) to the treatment month. We use *Platform Exposure* (intensive) as our baseline regressor in the second-stage regression and include *Platform Exposure* (extensive) results in the Appendix.

Table 4 displays the impact of the platform exposure on the treatment month *D(Stock Market Participation)*. In Columns (1) and (2), the samples, respectively, comprise those who have and those who have not participated in the stock market in one month before the treatment ($Dec18^{th} - Jan17^{th}$). We find that a unit increase in the platform exposure can raise the likelihood by 5.7% for those who have not participated in the stock market

in one month before the treatment, but it does not affect the stock market participation for those who have already participated before. Beyond being statistically significant, the economic magnitude of this effect is particularly noteworthy. Note that only 0.3% of the overall sample had participated in the stock market before the treatment, the 5.7% increase in participation for those previously inactive in the stock market reflects a considerable economic impact. The range of intensive platform exposure spans from 0 to 100, resulting in a potential impact range of up to a 570% increase in the likelihood of participation in the stock market.

The sample in Column (3)-the treated plus the matched control groups-excludes platform users who participated in the equity market in the pre-period. This restriction mitigates the likelihood that included individuals in our runs have unobserved historical platform exposure. The second stage regression shows that a unit increase in the platform exposure is associated with a 1.644% increase in an investor's equity holding share within her portfolio. Given that the average equity holding share in the sample is only 0.13% in one-month before the treatment, this 1.644% increase represents substantial economic effects, besides being statistical significance. Table A1 in the appendix shows that measuring the platform exposure using the extensive margin generates similar significant results that receiving the platform exposure can increase an investor's equity holding share by 0.66%. Tables 4 and A1 have an important policy implication: they support that a platform can increase novel investors' equity market participation via digital services that spread financial information and knowledge.

4.2.3 Second Stage: Investment Behaviors

We also investigate how the platform exposure (intensive margin) affects households' investment behaviors for the treated plus the matched control groups excluding platform users who participated in equity market in the pre-period. The primary investment outcomes are the monthly change in *Fund Balance, Fund Number, Fund Type, Automatic*

Investment Score, Allocation Score, and *Fund Holding Duration* which are measured by $(\bar{Y}_{Jan18^{th}-Feb17^{th},2023} - \bar{Y}_{Dec18^{th},2022-Jan17^{th},2023})$, the change from the month before the treatment to the treatment month.

Similar to the impact on the stock market participation, we find a significant and economically large increase in all users' investment behaviors, as shown in Table 5. For instance, a unit increase in the platform exposure leads to an average increase in the mutual fund balance by RMB 392 (around USD 54). Based on the range of the platform exposure ([0,100]), a potential impact range of up to RMB 39,200 (USD 5400). The number of holding funds and fund types also experience significant growth, highlighting the increase in portfolio diversification. Additionally, the platform exposure can improve the scores of portfolio allocation and automatic investment by 22.852 and 0.336, respectively. Compared to the average portfolio allocation and automatic investment scores prior to the treatment, these improvements represent a 9.18-fold increase in participants' portfolio allocation capabilities and an 11.20-fold rise in adopting automatic investment practices. Statistically, the weakness increase is for the *Fund Holding Duration*, which is significant only at the 10% level (5% for a one-tail test).

The impacts of the platform exposure measured by the extensive margin are also statistically significant and consistent with the baseline findings, as shown in Table A2. These results reveal that platform exposure can significantly enhance users' portfolio diversification and allocation skills and promote their automatic investment behavior, which can help investors avoid the challenge of determining the right time to invest and minimize the average cost of short-term investments.

4.3 Performance Before and After the Treatment

We analyze the short-term effects of the platform exposure on portfolio returns, focusing on a one-month time horizon. To assess performance, we follow Rossi and Utkus (2020), adopting the annualized abnormal Sharpe Ratio as our performance metric. This

metric compares an investor's realized Sharpe ratio to that of the market portfolio, represented by the SSE composite index in China. We annualize portfolio returns using daily portfolio returns and compute portfolio volatilities as realized volatilities using squared daily returns. However, investors who did not purchase any mutual funds during these timeframes are assigned an abnormal Sharpe ratio of zero.

The results, computed across all investors, are reported in Table 6. Column (1) shows that the average change in the abnormal Sharpe ratio from the 1-month before the treatment (Dec 18^{th} 2022-Jan 17^{th} 2023) to during the treatment month (Jan 18^{th}-Feb 17^{th} 2023) is significantly greater for the treated than the control group. Specifically, the treated group exhibits a 9.669-unit larger mean change in the abnormal Sharpe ratio from before to during the treatment each unit increase in the platform exposure, compared to the control group. This indicates a statistically significant effect and a considerable economic impact, suggesting that the platform exposure significantly enhances the risk-adjusted performance of the treated group relative to the control group during the treatment period. Column (2) shows that the platform exposure significantly raises the Sharpe ratio in the treatment month, even though it also increases users' portfolio volatility to a small degree. These results are consistent with the platform exposure's positive contributions to investment performance.

Due to data limitations, we cannot undertake longer time horizon studies (e.g., 3,6,9, and 12-month horizons). First, the probability of receiving additional rounds of marketing campaign materials from the platform is not random; we find that a recipient who has received the materials the month before is more likely to receive the materials again. The probability of continuously receiving promotion materials in consecutive marketing campaigns is likely affected by an investor's reaction (and resulting investment performance) to the initiating package of messages. Thus, promotion cannot be an exogenous instrument for anyone having received a message package in the previous month. We, therefore, cannot decompose the endogenous relation between platform exposure and an

investor's investment behavior after the person has received the first package of marketing messages. Second, even if we do not consider the issue of endogeneity to examine the impact of the platform's intended promotion of its digital financial services, the number of users who have received the continuous service promotions (i.e. 6-month) since the treatment month and also have invested in mutual funds, is insufficient for our investigation of investment performance.

4.4 Heterogeneous Effect of Platform Exposure Components

We also investigate how the platform exposure components (Personalized Robo-Advisor (PRA) and the three subcomponents of Wealth Community-Wealth Forum, Visual Content, and Other) affect users' investment decisions and whether these effects differ across different platform exposure components. We standardize the platform exposure components to a scale of 0 to 100 for comparability.

We use the estimated platform exposure components instrumented by the promotion dummy as the regressor of the second-stage regression in Eq.5. Figure 4 shows that all channels statistically significantly raise the probability of market participation, the fund balance, equity holding ratio, diversification (allocation score, fund number, fund type), and utilization of automatic investment plan. These channels' ability to raise fund holding duration is the weakest, but is still borderline significant. Finally, *Visual Content* has a significantly greater impact than all other platform exposure components. The result speaks to the power of visual impact on users.

4.5 Heterogenous effects of Platform Exposure

While the above results support that the promotion of digital transmission of financial knowledge and information positively impacts overall stock market participation and performance, the benefits may vary across sub-groups of users. Note that Figure 1 shows that a significant proportion of platform users who have not yet engaged in mutual fund

investments are older, less educated, and less wealthy. These individuals are more likely to experience financial illiteracy, have less investable resources, and are less prepared to comprehend and manage the risks of investing in stocks. Also, research indicates that lower-income households, constrained by liquidity issues, are typically reluctant to invest in perceived risky assets like stocks, prioritizing immediate financial needs over long-term investment opportunities (Lusardi and Mitchell, 2014). These groups may not even pay much attention to the promotion message and may not understand the transmitted messages. Yet, these groups' marginal gains in stock investing could be high. Therefore, one would hope that the transmission of financial literacy could particularly raise the stock market participation and investment performance of the older, less-educated, and those with less investable assets.

Hence, we explore the heterogeneity in the impact of the platform exposure across users' characteristics by repeating the baseline regressions from Table 3-5 across key demographic groups. Specifically, we categorized users by age (18-24, 25-49 and 50+), education level (without or with college education), and investable assets (below or above RMB 50,000). We also exclude from all these subsamples platform users with stock market participation in the pre-treatment period, for they inevitably already have mutual fund investment experience. The outcome variables include *Stock Market Participation* during the treatment month and the changes (treatment month vs. pre-treatment month) in *Equity Holding Ratio, Allocation Score, Automatic Investment Score, Fund Number, Fund Type, Fund Balance*, and *Abnormal Sharpe Ratio*. These variables capture three primary dimensions: investment engagement (measured by Stock Market Participation, Mutual Fund Balance, and Equity Holding Ratio), portfolio diversification (measured by Allocation Score, Fund Number, and Fund Type), and investment performance (measured by the Abnormal Sharpe Ratio).

Overall, our results suggest that digital transmission of financial knowledge and low-barrier access to stock market investment generate desirable financial inclusion: the older,

less educated, and less wealthy participate more in equity investment, with greater diversification and improved risk-adjusted returns. The result's details are as follows.

First, Figure 5 shows that the young, more educated and less wealthy are more likely to acquire the platform exposure when promoted to digital financial services. This trend can be attributed to several factors. Younger users are typically more tech-savvy and comfortable navigating digital platforms, making them more likely to engage with online financial education resources. Additionally, individuals with higher levels of education often possess stronger cognitive skills and a greater ability to comprehend complex financial concepts, which facilitates their learning through digital means. Meanwhile, the less wealthy may view digital financial education as an accessible and cost-effective opportunity to improve their financial literacy and investment outcomes, especially when traditional financial advisory services are expensive or inaccessible. Finally, promotion does not statistically raise the wealthier users' propensity to acquire platform exposure. The wealthier users may have already been introduced to stock investing by wealth management professionals.

Second, the impact of platform exposure is notable across nearly all demographic groups except for wealthier individuals. However, this impact varies among these groups, revealing the diverse needs of investors with different characteristics. Panel A to C of Figure 6 show the impacts of platform exposure on stock market participation and performance by sub-groups.

Panel A illustrates that stock market participation significantly increases across all age, education, and wealth groups, except for wealthier individuals. Notably, older, less educated, and less wealthy individuals also exhibit substantial growth in their mutual fund balances and equity holding ratios. These findings highlight that the digital dissemination of financial knowledge effectively reaches those traditionally less involved in risky assets and with limited investment capacity, enabling them to participate more actively in the stock market through increased mutual fund investments.

Furthermore, Panel B shows that digital financial education significantly enhances portfolio allocation capabilities across all demographic groups (except for the wealthier). However, its effect on portfolio diversification is particularly pronounced among older, less educated, and less wealthy individuals. For these groups, platform exposure increases the number and types of funds held, with the effects being more substantial than those observed in their younger, more educated and wealthier counterparts.

Finally, Panel C shows that the older, less educated, better educated and less wealthy individuals all exhibit significant improvements in investment performance. Again, the exception is the wealthier individuals. Interestingly, while platform exposure does not significantly raise the younger individuals' investment performance, it raises their adoption of automatic investment plans, enabling more streamlined investment decisions and potentially reducing long-term investment costs. The same positive impact is on the less educated and the less wealthy individuals. Thus, platform exposure not only enhances the willingness to increase stock investing for the older, younger, less educated, and less wealthy individuals but it also improves their investment capabilities by fostering better portfolio diversification and encouraging the adoption of automatic investment plans.

In summary, these results illustrate that digital financial education and low-barrier, low-cost means to invest in stocks benefit the older, less educated, and less wealthy. This is consistent with Reher and Sokolinski (2024), who show that Robot Advising is particularly helpful to less wealthy individuals. As a matter of fact, the benefitted subgroups are indeed more likely to need financial knowledge and are vulnerable to risky asset investment.

5 Robustness Check

We conduct a variety of robustness checks for the causal analysis of the platform exposure.

5.1 Another Measure for Investment Outcomes

In our baseline model, the primary investment outcomes are *D(Stock Market Participation)* (equals to 1 if the user i participated in the stock market during the treatment month) and the monthly change in *Equity Holding Ratio, Fund Balance, Fund Number, Fund Type, Allocation Score, Automatic Investment Score, and Fund Holding Duration*, measured by ($\bar{Y}_{Jan18^{th}-Feb17^{th},2023} - \bar{Y}_{Dec18^{th},2022-Jan17^{th},2023}$). For robustness check, we change the investment outcomes to be the $D(StockMarketParticipation)_{Feb17^{th}}$ (equals to 1 if the user i participated in the stock market on $Feb17^{th}$, the last day of the treatment month), and the change in *Equity Holding Ratio, Fund Balance, Fund Number, Fund Type, Allocation Score, Automatic Investment Score, and Fund Holding Duration*, which is measured by ($Y_{Feb17^{th}}$-$Y_{Jan17^{th}}$) from the day right before the treatment ($Jan17^{th}$) to the last day of the treatment month ($Feb17^{th}$).

Besides the measure for the investment outcomes, everything else remains unchanged from the baseline research setting. Table A4-A5 show that the 2SLS results are similar to the baseline and the impact of *Platform Exposure* on investment outcomes remained statistically significant positive except for *Fund Holding Duration*. The lack of impact on *Fund Holding Duration* when measured using the ending day of the treatment month may be attributed to the inherent volatility of fund holding duration within a given month. As a result, the monthly average value provides a more comprehensive representation, effectively capturing the variations and overall trends in users' fund holding behavior.

5.2 Other Measures for Platform Exposure

We also measure digital platform exposure based on the total number of days users interacted with the primary digital financial information channels, including the PRA, the wealth community, and its subcomponents—the forum, visual content (comprising short videos and image-text), and the super-topic section. This alternative measure provides a more comprehensive perspective, offering greater granularity in capturing users' interac-

tions with the platform exposure.

We use the min-max approach used by Lyons and Kass-Hanna (2021) to measure the platform exposure using these six components with equal weighting. The platform exposure is computed using the following equations in this method:

$$Platform\ Exposure_{alternativei} = \frac{\sum_{f=1}^{F} \frac{actual\ value_{fi} - minimum\ value_f}{maximum\ value_f - minimum\ value_f}}{F} * 100 \qquad (6)$$

where i represents the sample individual; f is the included component to measure the digital platform exposure; F is the total number of the included components; $maximum\ value_f$ and $minimum\ value_f$ are, respectively, the maximum and minimum value of component f among the whole sample users. However, if an individual has not used any of the six services, we mark her $PlatformExposure_i$ as zero.

Then, we use the $Platform\ Exposure_{alternative}$ to re-estimate the impact of the platform exposure on users' investment outcomes following the baseline 2SLS regressions. Table A6-A8 produce results consistent with our baseline model, suggesting that the measurement method for platform exposure does not alter its significantly positive impact on investment outcomes.

6 Conclusions

Digital platform exposure refers to delivering current financial knowledge and financial product information to investors through digital means and networks. It also connects product providers and the investor community. This paper examines whether such platform exposure can enhance households' stock market participation, investment behaviors, and investment performance. Given the widespread adoption of such digital financial services and the prevalence of low stock market participation, this paper can help policymakers understand the potential advantages of financial learning through digital platforms,

which could improve household welfare and foster effective financial inclusion.

By exploiting a quasi-experimental research design, we find that the digital platform exposure indeed has a positive effect on households' stock market participation and financial behaviors. The exposure increases household investment in stock-based mutual funds for extended periods, builds up more diverse portfolios and reduces short-term investment costs. Beyond such investment behaviors, platform exposure also increases investors' investment performance, such as the abnormal Sharpe ratio of their investment portfolio.

This study also demonstrates that the impact of digitally transmitted financial knowledge on investment decisions varies across demographic groups. The findings reveal that those who are young, more educated and less wealthy are more likely to gain platform exposure through digital financial services promotion. The effect is particularly pronounced among older, less educated, and less wealthy individuals across the three dimensions—investment engagement, portfolio diversification, and performance. These sub-groups represent a substantial portion of platform users with no prior mutual fund investment, and they are more likely to face substantial barriers to stock market participation. Therefore, the results highlight that digital financial education raises financial inclusion.

Our paper has significant implications for policy and financial education initiatives. Transmitting financial knowledge to stock investing via digial platforms is a low-cost, scalable, and impactful alternative to traditional approaches. This is particularly important given the widespread lack of financial literacy globally. Moreover, the varying impacts of financial knowledge across diverse user profiles highlight the necessity of tailoring educational content to individual needs.

This paper is a beginning attempt to study the effects of learning finance via digital platforms on household investment behavior and performance. While the results are positive and intuitively appealing, the long-term effects of the platform exposure need

further investigation. Additionally, there could be unexplored costs and unexpected consequences, e.g., self-interested service providers can take advantage of digital platform exposure to exploit non-suspicious users. More studies are necessary to fully understand the mechanism of the platform exposure's effects on household welfare.

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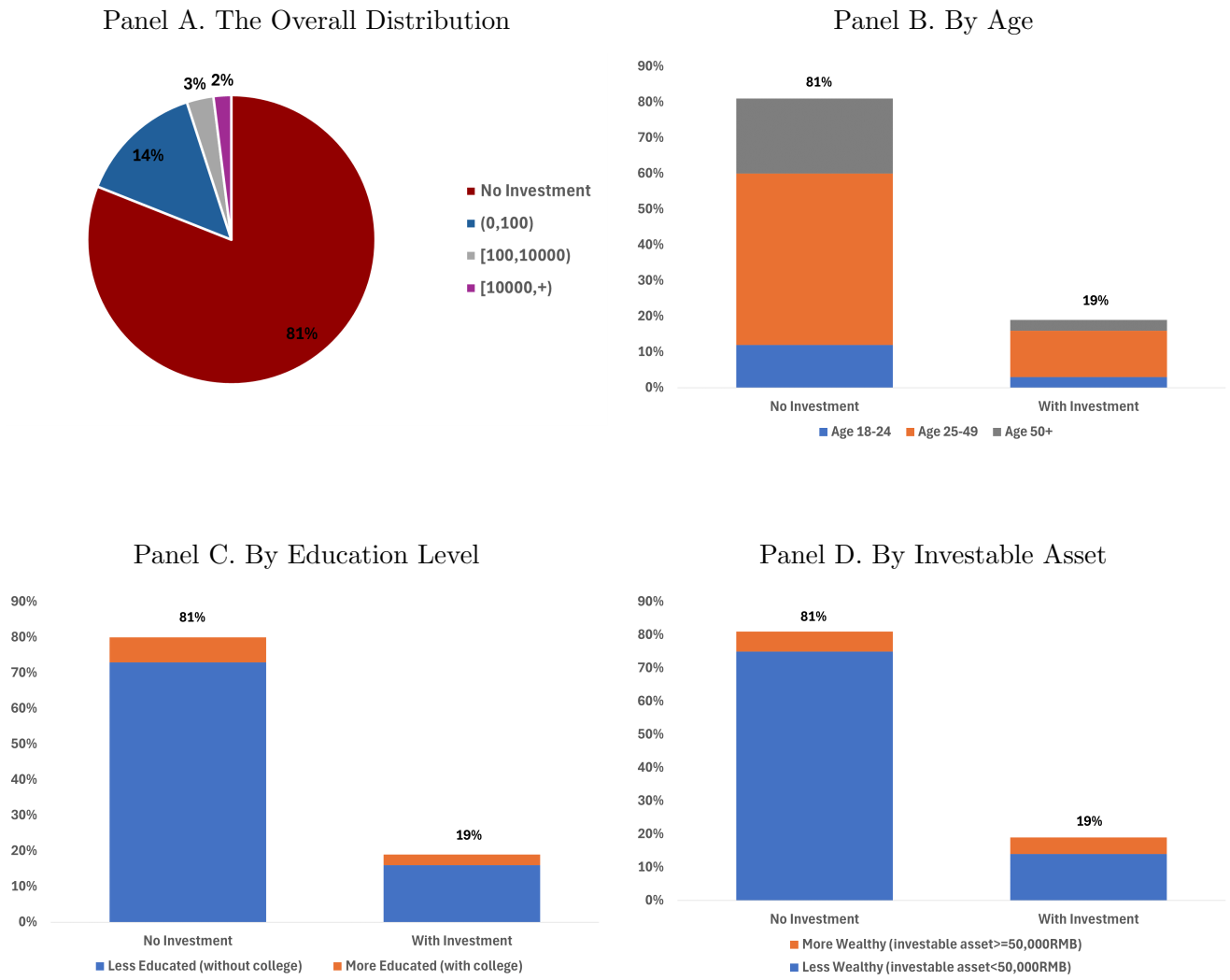
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Figure 1: Distribution of Platform Users Across Mutual Fund Balance Categories

This figure illustrates the distribution of platform users aged 18 and older across four categories of mutual fund balances as of December 2022. The categories are: (1) No Investment (no mutual fund balance), (2) RMB (0, 100), (3) RMB [100, 10,000), and (4) RMB 10,000 or above. Panel A shows the overall distribution, while Panels B-D display the breakdown by age, education level, and investable asset groups, respectively, distinguishing users with and without mutual fund investments. Note that "More Educated" refers to those with a bachelor's degree or higher, while "Less Educated" includes those with lower education levels. "More Wealthy" are individuals with investable assets greater than or equal to 50,000 RMB, and "Less Wealthy" have assets below this threshold.



Source: Calculations are based on platform data (1 RMB = 0.14 USD).

Figure 2: January Marketing Campaign Timeline

This figure displays the timeline of the marketing campaign starting on January 18^{th}. The measure for the *Promotion*, *Platform Exposure* and investment outcomes are based on this timeline.



Figure 3: Matched Sample - Parallel Trend in Investment outcomes

This figure illustrates the parallel trends in investment outcomes for treated users and their matched counterparts. The investment outcomes analyzed include the *Allocation Score, Automatic Investment Score, Fund Number, Fund Type, Fund Balance, and Equity Holding Ratio*. The vertical axis represents the net difference in the monthly average investment outcomes between treated and non-treated users. To standardize comparisons, the mean difference for each month is divided by the mean difference in January (the treatment month) and scaled by 100. The horizontal axis denotes the timeline in months, spanning from October 18^{th} 2022 to July 17^{th} 2023, for all outcomes. The area between the orange vertical dotted lines marks the treatment period, defined as January 18^{th} to February 17^{th} 2023.

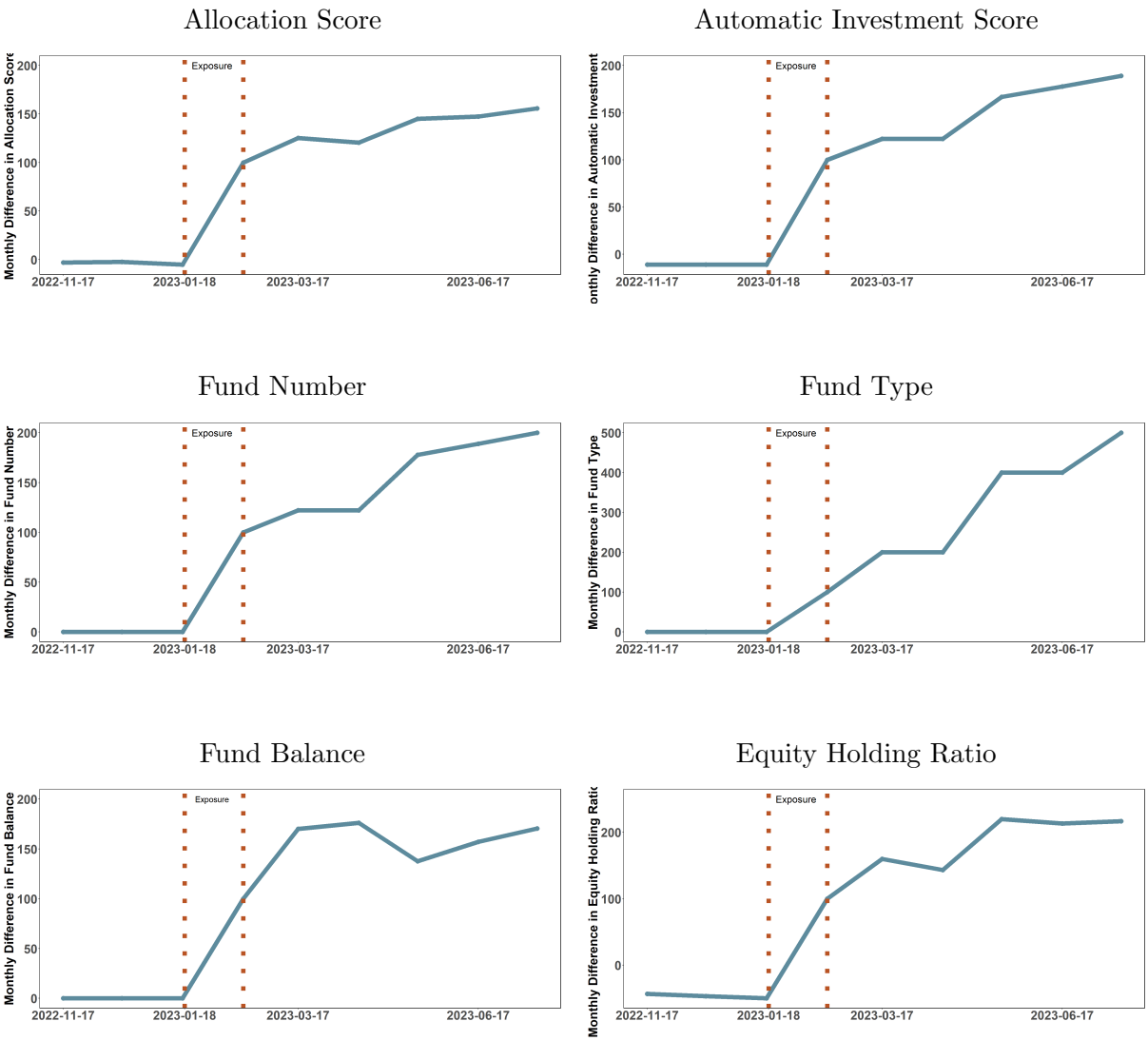


Figure 4: Heterogeneous Impact of Platform Exposure Components on Investment Outcomes

This figure illustrates the heterogeneous impact of different subcomponents of platform exposure (measured by the natural logarithm of (1+ monthly visiting time)) on investment outcomes for the matched sample, excluding users who participated in the stock market prior to the treatment month. Platform exposure is categorized into "Personalized Robo-Advisor (PRA)" and the "Wealth Community", which is further divided into three subcomponents: "Wealth Forum", "Visual Content", and "Other". "Visual Content" includes short videos and image-text content, while Other encompasses financial content not classified under "Wealth Forum" or "Visual Content". The primary investment outcomes are *Stock Market Participation, Equity Holding Ratio, Allocation Score, Automatic Investment Score, Fund Number, Fund Type, Fund Balance, Abnormal Sharpe Ratio* and *Fund Holding Duration*. The vertical axis represents the coefficient estimates and associated 95% confidence intervals of the second-stage regression model: $Y_i = \alpha + \beta \widehat{C}_i + \varepsilon_i$, where $\widehat{C}_i$ denotes the instrumented platform exposure or its subcomponents. The horizontal axis shows the platform exposure and its subcomponents, with t-statistics based on user-level clustered standard errors.

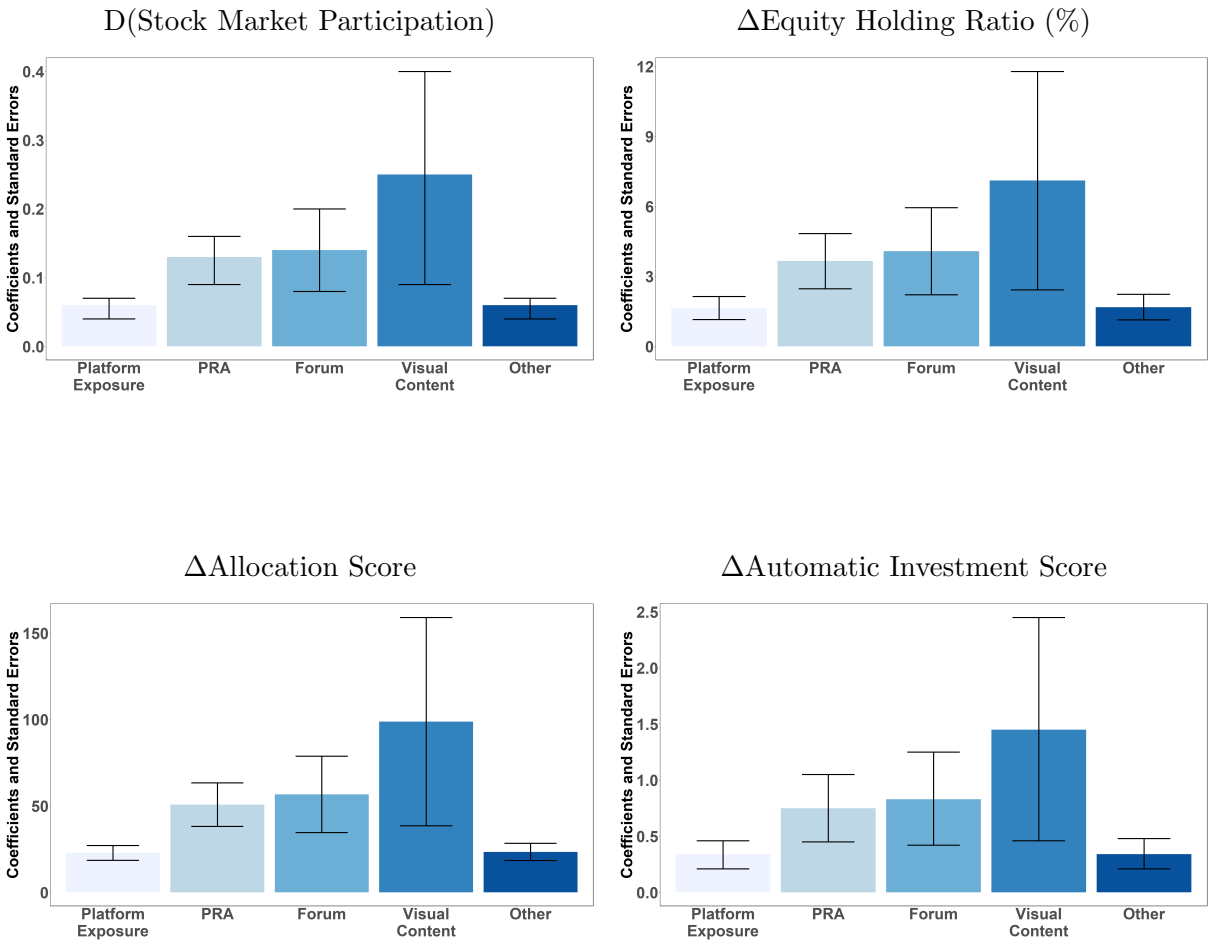


Figure 4: Heterogeneous Impact of Platform Exposure Components on Investment Outcomes (Continued)

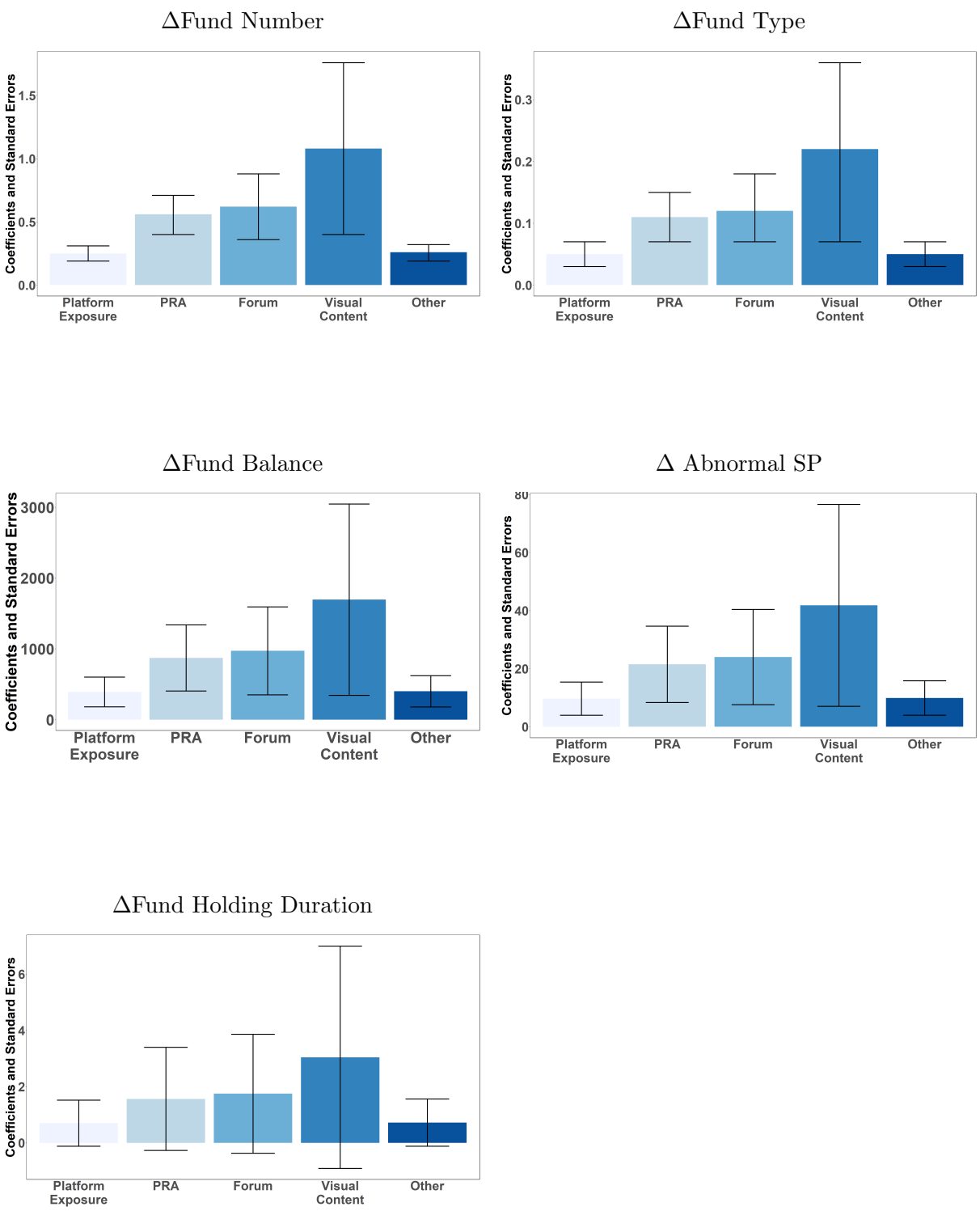


Figure 5: Heterogeneous Platform Exposure (Intensive) Across Users' Characteristics

This figure reports the heterogeneous effect of service promotion on the acquisition of the platform exposure across various characteristics. The vertical axis represents the coefficient estimates and associated 95% confidence intervals of the first-stage regression model: $PlatformExposure_i = \alpha + \theta \mathbb{1}\{Promotion\}_i + \varepsilon_i$. The first bar represents estimates based on the entire matched sample. The remaining bars display subgroup estimates based on users' age (18-24, 25-49, and 50+), education level (without vs. with a college degree), and investable asset level (below vs. above 50,000 RMB).

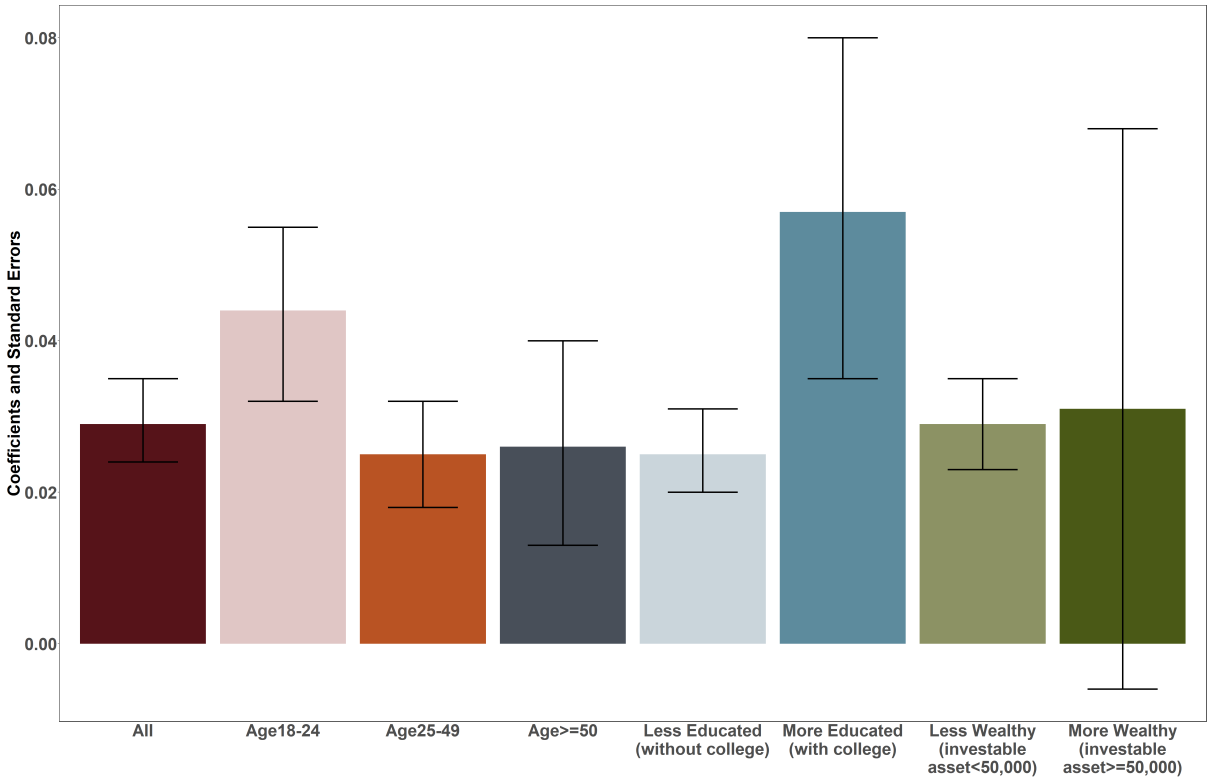


Figure 6: Heterogeneous Impact of Platform Exposure Across Users' Characteristics

This figure illustrates the heterogeneous effect of platform exposure on investment outcomes across different user characteristics: age, education, and investable asset level. The investment outcomes are grouped into three dimensions: investment engagement (Panel A), including *Stock Market Participation (Dummy), Equity Holding Ratio, Fund Balance*; portfolio diversification (Panel B), including *Allocation Score, Fund Number, Fund Type*; and investment performance (Panel C), including *Abnormal Sharpe Ratio* and *Automatic Investment Score*. The vertical axis represents the coefficient estimates and associated 95% confidence intervals of the second-stage regression model: $Y_i = \alpha + \beta \widehat{Platform Exposure}_i + \varepsilon_i$.

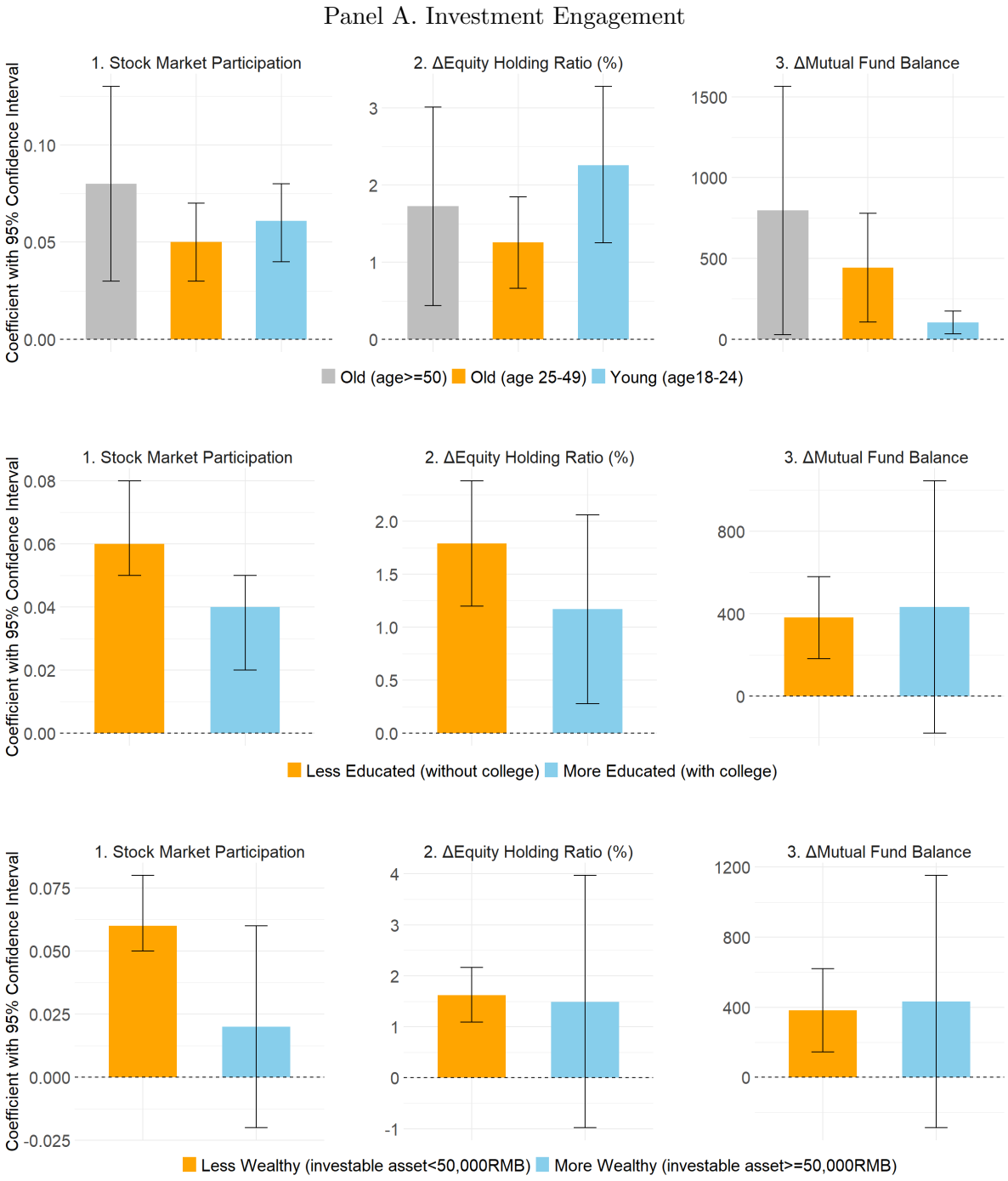


Figure 6: Heterogeneous Impact of Platform Exposure Across Users' Characteristics (Continued)

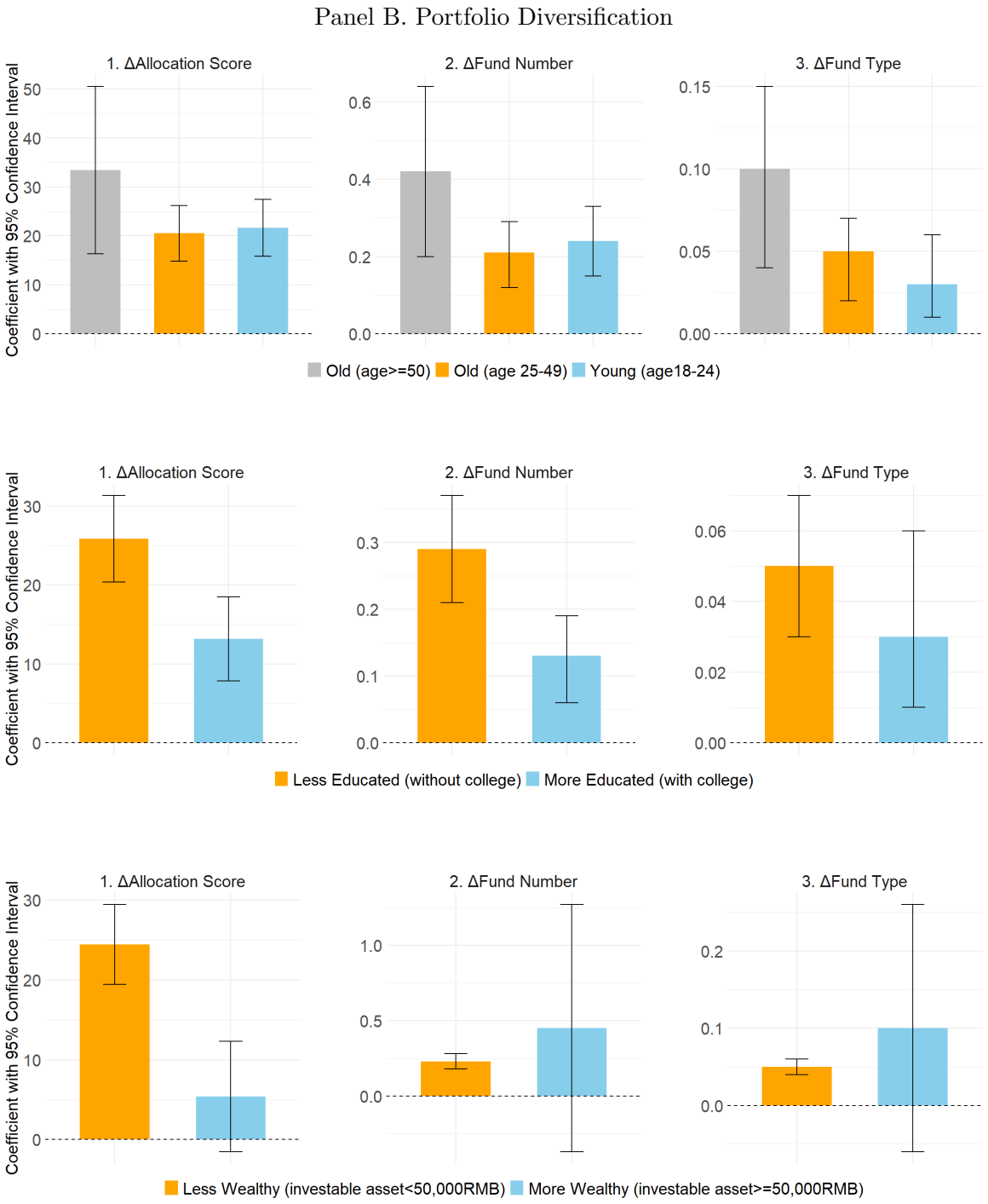


Figure 6: Heterogeneous Impact of Platform Exposure Across Users' Characteristics (Continued)

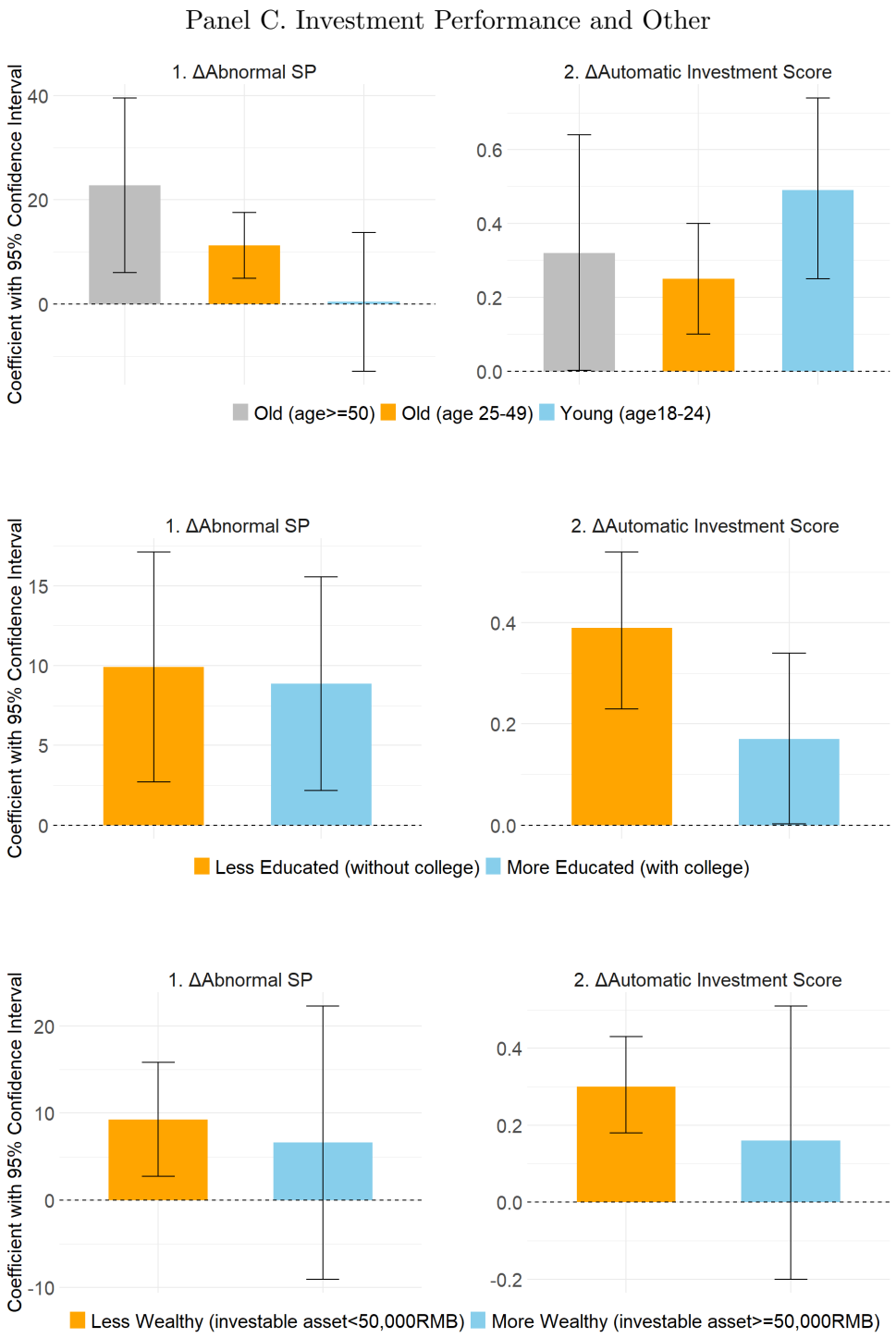


Table 1: Balancing of Characteristics Across Treated and Non-Treated Users

This table presents cross-sectional summary statistics for treated (Panel A) and control users (Panel B). We report the mean, standard deviation, and percentiles (1st, 25th, 50th, 75th, and 99th). Key demographic variables include: *Age*, user age as of end-2022; *Gender*, with 1 for males and 0 for females; *High Education*, a binary variable for users with a bachelor's degree or higher; *Fund Investment Experience*, total months invested in the fund market; and *Investable Asset>= CN¥5W*, a dummy for users with investable assets of ¥50,000 RMB (around 6,824 USD) or above. Investment behavior variables are calculated over the three months prior to the campaign (January 18, 2023), including: *Fund Balance*, the average balance of mutual funds; *Fund Number*, the average number of funds held by the portfolio; *Fund Type*, the average number of fund types in the portfolio; *Fund Holding Duration*, the average maturity of holding funds with the unit of day; *Allocation score* and *Automatic Investment Score* are computed by the wealth team to measure the capability of allocating portfolios and the degree of automatic investment, respectively (for detailed calculations, see Appendix A.1); *Risk Level* is measured by investors' answers to the platform's risk survey and represents risk tolerance, ranging from 0 to 5; *Equity Holding Ratio*, the average share of equity in the portfolio.

	Mean	SD	P1	P25	P50	P75	P99
Panel A. Treated							
Age	36.89	12.51	18	26	35	46	69
Gender	0.57	0.49	0	0	1	1	1
High Education	0.12	0.33	0	0	0	0	1
Fund Investment Experiences (month)	1.64	7.85	0	0	0	0	47
Investable Asset>= CN¥5W (Dummy)	0.05	0.23	0	0	0	0	1
Fund Balance	0.41	30.46	0	0	0	0	1.01
Fund Number	0.04	0.49	0	0	0	0	1
Fund Type	0.01	0.20	0	0	0	0	0
Automatic Investment Score	0.07	1.20	0	0	0	0	0
Allocation Score	3.24	8.41	0	0	0	0	35
Fund Holding Duration	0.58	15.93	0	0	0	0	0
Risk Level	0.86	1.14	0	0	0	2	4
Equity Holding Ratio (%)	0.22	4.01	0	0	0	0	0
Panel B. Non Treated (Pre Matching)							
	t-test	Mean	SD	P1	P25	P50	P75	P99
Age	0.16	36.88	12.52	18	26	35	46	69
Gender	0.00	0.57	0.49	0	0	1	1	1
High Education	0.00	0.12	0.33	0	0	0	0	1
Fund Investment Experiences (month)	0.15	1.63	7.86	0	0	0	0	47
Investable Asset> CN¥5W (Dummy)	0.00	0.05	0.23	0	0	0	0	1
Fund Balance	4.06	0.02	0.82	0	0	0	0	0
Fund Number	2.68	0.04	0.47	0	0	0	0	1
Fund Type	-0.69	0.01	0.21	0	0	0	0	0
Automatic Investment Score	0.13	0.07	1.19	0	0	0	0	0
Allocation Score	19.40	2.54	7.74	0	0	0	0	35
Fund Holding Duration	0.28	0.56	15.41	0	0	0	0	0
Risk Level	1.21	0.86	1.13	0	0	0	2	4
Equity Holding Ratio (%)	1.11	0.20	3.88	0	0	0	0	0

Table 2: Matching Sample Distribution

This table presents cross-sectional summary statistics for a matched sample of 180,186 platform users. We report the mean difference between treated and matched non-treated groups, t-statistics for equality of means, and summary statistics (mean, standard deviation, 1st, 25th, 50th, 75th, and 99th percentiles) for the whole matched sample. Panel A covers demographic characteristics: *Age* (user age as of end-2022), *Gender* (1 for males, 0 for females), *High Education* (binary variable for users with a bachelor's degree or higher), *Fund Investment Experience* (total months invested in funds), and *Investable Asset>= CN¥5W* (dummy for investable assets greater than or equal to ¥50,000 RMB). Panel B and C cover the 3-month average of users' investment behaviors and engagement in risky asset markets (October 18^{th} 2022 to Jan 17^{th} 2023): *Fund Balance*, *Fund Number*, *Fund Type*, *Fund Holding Duration*, *Allocation Score*, *Automatic Investment Score*, *Risk Level* (measuring risk tolerance, 0-5), and *Equity Holding Ratio*, *Stock Market Participation* (1 if the user has purchased stock-based funds) and *Mutual Fund Investment* (1 if the user has invested in mutual funds).

	Mean Diff	t-stat	Mean	SD	P1	P25	P50	P75	P99
Panel A. Demographic Characteristics									
Age	0.00	0.00	36.50	12.72	18	26	35	45	68
Gender	0.00	0.00	0.57	0.50	0	0	1	1	1
High Education	0.00	0.00	0.12	0.33	0	0	0	0	1
Fund Investment Experiences (month)	0.07	1.30	1.41	7.21	0	0	0	0	38
Investable Asset>= CN¥5W (Dummy)	0.00	0.00	0.05	0.2	0	0	0	0	1
Panel B. Investment Behaviors									
Fund Balance	0.0004	0.20	0.01	0.34	0	0	0	0	0.07
Fund Number	0.0002	0.13	0.03	0.29	0	0	0	0	1
Fund Type	-0.0002	-0.26	0.01	0.16	0	0	0	0	0
Automatic Investment Score	-0.001	-0.23	0.03	0.77	0	0	0	0	0
Allocation Score	-0.02	-0.57	2.49	7.34	0	0	0	0	35
Fund Holding Duration	-0.07	-1.31	0.35	12.14	0	0	0	0	0
Risk Level	0.01	1.17	0.87	1.14	0	0	0	2	4
Equity Holding Ratio (%)	-0.01	-0.96	0.13	3.12	0	0	0	0	0
Panel C. Engagement in Risky Asset Markets									
D(Stock Market Participation)	-0.0002	-0.86	0.003	0.05	0	0	0	0	0
D(Mutual Fund Investment)	0.00	0.00	0.008	0.09	0	0	0	0	0

Table 3: First Stage - Acuqisition of Platform Exposure

This table shows coefficient estimates and associated t-statistics (in parentheses) of the following regression model based on the matching sample:

$$Intensive : PlatformExposure_i = \alpha + \theta \mathbb{1}\{Promotion\}_i + \varepsilon_i$$

$$Extensive : \mathbb{1}\{PlatformExposure\}_i = \alpha + \theta \mathbb{1}\{Promotion\}_i + \varepsilon_i$$

where *Platform Exposure* is measured by extensive and intensive margins; Platform Exposure$_i$ is the level of the platform exposure gained by the user i; and $\mathbb{1}\{PlatformExposure\}_i$ is a dummy variable equal to 1 if the user i has used digital financial services to acquire the platform exposure during the treatment month and 0 otherwise. $\mathbb{1}\{Promotion\}_i$ is set to 1 for the users randomly assigned to receive the service promotion during the January campaign. Column (1) and (2) display the platform exposure in extensive and intensive margins, respectively. We report t-statistics based on standard errors clustered at the individual level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Platform Exposure	
	Intensive	Extensive
$\mathbb{1}\{Promotion\}_i$	0.029***	0.014***
	(10.90)	(33.87)
Adj R^2	0.01	0.01
Obs	180,186	180,186
Kleibergen-Paap F-stat	118.76	1147.11

Table 4: Second Stage - Effect of Platform Exposure (Intensive) on Stock Market Participation

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample:

$$Y_i = \alpha + \beta \widehat{PlatformExposure_i} + \varepsilon_i$$

where Y_i represents one of two outcomes: *D(Stock Market Participation)*, a binary indicator equal to 1 if user i participated in the stock market during the treatment (starting Jan 18), and Δ *Equity Holding Ratio*, which measures the change in the equity share held by user i before and during the treatment. The change is calculated by subtracting the average equity holding ratio from Dec 18, 2022–Jan 17, 2023 (pre-treatment) from the average ratio from Jan 18–Feb 17, 2023 (during treatment). Column (1) and (2) show the impact of platform exposure on *D(Stock Market Participation)* for users who participated and did not participate in the stock market in the month before the treatment, respectively. Column (3) shows the impact of platform exposure on Δ *Equity Holding Ratio* for treated and matched control users, excluding those who participated in the stock market before the treatment. Platform exposure is instrumented using $\mathbb{1}Promotion_i$, a binary variable set to 1 for users randomly assigned to receive the service promotion during the treatment. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	D(Stock Market Participation)		Δ Equity Holding Ratio (%)
	(1)	(2)	(3)
$Platform \quad Exposure_i$	-0.013	0.057***	1.644***
	(-0.07)	(8.05)	(6.49)
Sample	SMP before the treatment	No SMP before the treatment	No SMP before the treatment
Obs	451	179,735	179,735

Table 5: Second Stage - Effect of Platform Exposure (Intensive) on Investment Behaviors

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample excluding those who have participated in the stock market before the treatment month:

$$Y_i = \alpha + \beta \widehat{PlatformExposure_i} + \varepsilon_i$$

where Y_i represents one of six outcomes, each measuring the monthly average change from the month before the treatment (Dec 18, 2022–Jan 17, 2023) to the month during the treatment (Jan 18–Feb 17, 2023): Δ*Fund Balance*, Δ*Fund Number*, Δ*Fund Type*, Δ*Allocation Score*, Δ*Automatic Investment Score*, and Δ*Fund Holding Duration*. These variables capture the change in mutual fund balance, number of funds, distinct fund types, portfolio allocation capability, degree of automatic investment, and fund holding duration, respectively. We instrument platform exposure using $\mathbb{1}Promotion_i$, a binary variable set to 1 for users randomly assigned to receive the promotion during the treatment. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	ΔFund Balance	ΔFund Number	ΔFund Type	ΔAutomatic Investment	ΔAllocation Score	ΔFund Holding Duration
	(1)	(2)	(3)	(4)	(5)	(6)
Platform Exposure$_i$	392.114***	0.250***	0.050***	0.336***	22.852***	0.704*
	(3.65)	(8.13)	(5.32)	(6.00)	(10.44)	(1.68)
Obs	179,735	179,735	179,735	179,735	179,735	179,735

Table 6: Abnormal Sharpe Ratio Before and After the January Campaign

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample excluding those who have participated in the stock market before the treatment month:

$$Y_i = \alpha + \beta \widehat{PlatformExposure_i} + \varepsilon_i$$

where Y_i represents the investment performance change from the month before (Dec 18–Jan 17) to the treatment month (Jan 18–Feb 17) for user i. Performance is measured by the abnormal Sharpe Ratio, following Rossi and Utkus (2020), as the difference between the investor's Sharpe ratio and the market portfolio's Sharpe ratio (SSE Composite Index). Portfolio returns are annualized, and volatilities are based on daily squared returns. For users with no mutual fund investment, the abnormal Sharpe Ratio is set to zero. Column (1) reports the impact of the platform exposure on the mean difference in abnormal Sharpe ratios between 1 month before and during the treatment; Column (2) reports the Sharpe ratio during the treatment; and Column (3) shows the impact on daily portfolio volatilities during the treatment. Platform exposure is instrumented using $\mathbb{1}Promotion_i$, a dummy set to 1 for users randomly assigned to the promotion during the campaign. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	Mean Diff (Abnormal SP)	Sharpe Ratio	Volatility
	(1)	(2)	(3)
$PlatformExposure_i$	9.669***	10.820***	0.001***
	(3.32)	(3.74)	(9.37)
Obs	179,735	179,735	179,735

A Appendix

A.1 Detailed Descriptions for Some Outcome Variables

Allocation Score: A score is computed by the platform investment team as follows:

1) if the user does not hold any asset including money market funds, fixed-term products and mutual funds, then 0;

2) if the user only has the positive balance in money market funds but does not hold any other kinds of assets, then 20;

3) if the user only has the positive platform's fixed-term products but does not hold any other kinds of assets, then 25;

4) if the user only has the positive balance in both money market funds and fixed-term deposits but does not hold any other kinds of assets, then 30;

5) if the user has held mutual funds whose balance is greater than 0 but less than 100 RMB, then 35;

6) if the user has held mutual funds and

- mutual fund balance is equal to or greater than 100 RMB;
- $equity\ ratio + bond\ ratio > 0$;
- $equity\ ratio_{lower\ bound} <= \frac{equity\ ratio}{equity\ ratio+bond\ ratio} <= equity\ ratio_{upper\ bound}$;
- $current\ gold\ ratio >= gold\ ratio_{lower\ bound}$;

then 100;

7) if the user has held mutual funds and

- mutual fund balance is equal to or greater than 100 RMB;
- risk level that ranges from 0 to 5 in the platform is 0;
- $current\ equity\ ratio = 0$
- $current\ bond\ ratio = 0$
- $current\ gold\ ratio = 0$

then 100;

8) if the user has held mutual fund balance that is equal to or greater than 100 and does not satisfy the condition (6) and (7), then the score is

$$30 + [1 - \sqrt{\frac{(equity\ ratio_r - equity\ ratio)^2 + (bond\ ratio_r - bond\ ratio)^2 (gold\ ratio_r - gold\ ratio)^2}{2}}]$$

where $equity\ ratio_r$, $bond\ ratio_r$, $gold\ ratio_r$ are the platform's recommended ratio;

Automatic Investment Score: A score is computed by the platform investment team as follow:

1) If the user never signed up for the automatic investment plan, then 0;

2) If the user has ever signed up for the automatic investment plan but is currently not in the plan, then 20;

3) If the user has signed up for the automatic investment plan and currently has investments through automatic investing, then the score is

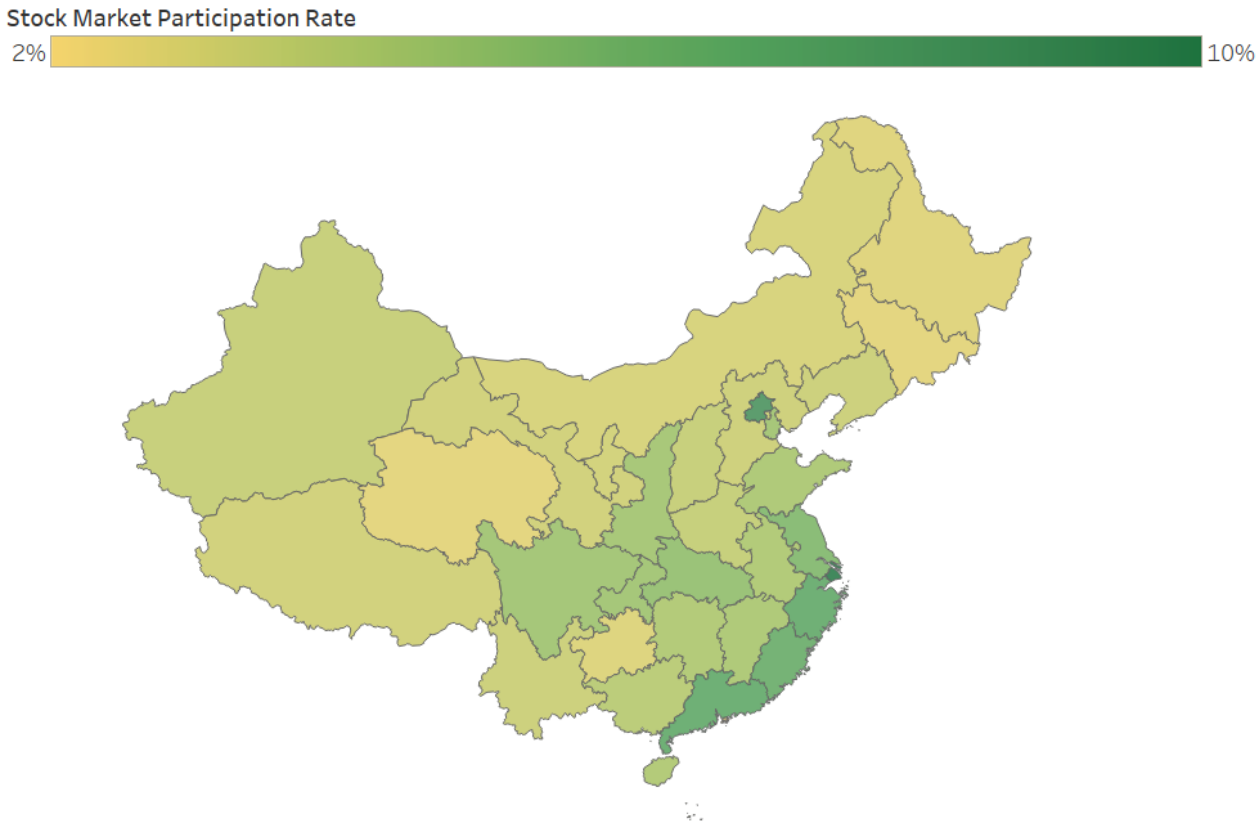
$$30 + \lfloor \frac{\#fix - buy\ funds}{\#total\ funds} * 50 \rfloor + min(\#fix - buy\ funds, 5) * 4$$

A.2 Platform Users' Stock Market Participation (Province Level)

As of December 2022, only 5% of the platform users (over 1 billion) invested in the stock market through equity-based mutual funds, as depicted in Figure A1. Although Shanghai (China's largest city and a global financial hub) has the highest indirect stock market participation rate of 10.4% through the platform we analyzed, the rate is still significantly lower than that of the United States, which stands at 55%. Along with China's significant growth in online investment platforms and their diverse information channels, which have made accessing the stock market through mutual funds more accessible and affordable, the digital transmission of financial knowledge could thus be instrumental in raising households' stock market participation.

Figure A1: Stock Market Participation Rate of Platform Users

This figure displays the percentage of the whole platform users participating in the stock market in China through purchasing equity-based funds at the beginning of December 2022.



Source: All calculations are based on data obtained from the platform we analyzed.

Table A1: Second Stage - Effect of Platform Exposure (Extensive) on Stock Market Participation

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample:

$$Y_i = \alpha + \beta \widehat{\mathbb{1}\{PlatformExposure\}_i} + \varepsilon_i$$

where Y_i represents one of the two outcomes: *D(Stock Market Participation)*, a dummy equals to 1 if user i has ever participated in the stock market during the treatment (January campaign starting on Jan 18^{th}), and Δ *Equity Holding Ratio* measures the change in the share of equity held by user i in the group g before and during the treatment. It is computed by using the monthly average equity holding ratio from Jan 18^{th} to Feb 17^{th}, 2023 (during the treatment) to subtract the monthly average equity holding ratio from Dec 18^{th} 2022 to Jan 17^{th} 2023 (before the treatment). Column (1) and (2) show the impact of the platform exposure on *D(Stock Market Participation)* for those who have participated in the stock market in one month before the treatment (Dec 18^{th} 2022 to Jan 17^{th} 2023) and those who have not participated before, respectively. Column (3) shows the impact of the platform exposure on Δ *Equity Holding Ratio* for the treated and matched control users excluding those who have participated in the stock market in one month before the treatment (Dec 18^{th} 2022 to Jan 17^{th} 2023). We instrument $\mathbb{1}\{PlatformExposure\}_i$ with $\mathbb{1}\{Promotion\}_i$ which is a dummy variable set to 1 during the treatment only for users randomly assigned to receive the service promotion. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	D(Stock Market Participation)		ΔEquity Holding Ratio
	(1)	(2)	(3)
$\mathbb{1}\{PlatformExposure\}_i$	-0.037	0.123***	3.538***
	(-0.07)	(10.88)	(7.68)
Sample	SMP before the treatment	No SMP before the treatment	No SMP before the treatment
Obs	451	179,735	179,735

Table A2: Second Stage - Effect of Platform Exposure (Extensive) on Investment Behaviors

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample excluding those who have participated in the stock market before the treatment month:

$$Y_i = \alpha + \beta \mathbb{1}\{\widehat{PlatformExposure}\}_i + \varepsilon_i$$

where Y_i represents one of the six outcomes that are measured by the monthly average level change from the month before (Dec 18^{th} 2022-Jan 17^{th} 2023) to the month during the treatment (Jan 18^{th}-Feb 17^{th} 2023): Δ*Fund Balance*, the monthly average change in the mutual fund balance of user i from the month before the treatment to the month during the treatment; Δ*Fund Number*, the the monthly average change in the number of funds held by user i from the month before the treatment to the month during the treatment; Δ*Fund Type*, the monthly average change in the number of distinct fund types held by user i from the month before the treatment to the month during the treatment; Δ*Allocation score* and Δ*Automatic Investment Score*, the monthly average change in the capability of allocating portfolios and the degree of automatic investment by user i from the month before the treatment to the month during the treatment; Δ*Fund Holding Duration*, the monthly average change in the maturity of holding funds by user i from the month before the treatment to the month during the treatment. We instrument $\mathbb{1}\{$*Platform Exposure*$\}_i$ with $\mathbb{1}\{$*Promotion*$\}_i$ which is a dummy variable set to 1 during the treatment only for users randomly assigned to receive the service promotion. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	ΔFund Balance	ΔFund Number	ΔFund Type	ΔAutomatic Investment	ΔAllocation Score	ΔFund Holding Duration
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{PlatformExposure\}_i$	843.851***	0.538***	0.108***	0.723***	49.178***	1.514*
	(3.81)	(10.96)	(6.62)	(5.97)	(25.20)	(1.70)
Obs	179,735	179,735	179,735	179,735	179,735	179,735

Table A3: Second Stage - Effect of Platform Exposure (Extensive) on Investment Performance

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample excluding those who have participated in the stock market before the treatment month:

$$Y_i = \alpha + \beta \widehat{\mathbb{1}\{PlatformExposure\}_i} + \varepsilon_i$$

where Y_i represents the investment performance change from the month before (Dec 18–Jan 17) to the treatment month (Jan 18–Feb 17) for user i. Performance is measured by the abnormal Sharpe Ratio, following 2020, as the difference between the investor's Sharpe ratio and the market portfolio's Sharpe ratio (SSE Composite Index). Portfolio returns are annualized, and volatilities are based on daily squared returns. For users with no mutual fund investment, the abnormal Sharpe Ratio is set to zero. Column (1) reports the impact of the platform exposure on the mean difference in abnormal Sharpe ratios between 1 month before and during the treatment; Column (2) reports the Sharpe ratio during the treatment; and Column (3) shows the impact on daily portfolio volatilities during the treatment. We instrument $\mathbb{1}\{Platform\ Exposure\}_i$ with $\mathbb{1}\{Promotion\}_i$ which is a dummy variable set to 1 during the treatment only for users randomly assigned to receive the service promotion. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	Mean Diff (Abnormal SP)	Sharpe Ratio	Volatility
	(1)	(2)	(3)
$PlatformExposure_i$	20.807***	23.286***	0.003***
	(3.46)	(3.95)	(16.02)
Obs	179,735	179,735	179,735

Table A4: Robustness I (Different Measure): Second Stage - Effect of Platform Exposure (Intensive) on Stock Market Participation

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample:

$$Y_i = \alpha + \beta \widehat{PlatformExposure_i} + \varepsilon_i$$

where Y_i represents one of the two outcomes: *D(Stock Market Participation)*, a dummy equals to 1 if user i has participated in the stock market on Feb 17^{th}, the day at the end of the treatment; and Δ *Equity Holding Ratio*, is Equity Holding Ratio$_{Feb17^{th}}$-Equity Holding Ratio$_{Jan17^{th}}$, computed by subtracting the equity holding ratio on Jan 17^{th} 2023 (the day before the treatment) from the equity holding ratio on Feb 17^{th} (the day at the end of the treatment) for user i. Column (1) and (2) show the impact of the platform exposure on *D(Stock Market Participation)* for those who have participated in the stock market in one month before the treatment (Dec 18^{th} 2022 to Jan 17^{th} 2023) and those who have not participated before, respectively. Column (3) shows the impact of the platform exposure on Δ *Equity Holding Ratio* for the treated and matched control users excluding those who have participated in the stock market in one month before the treatment (Dec 18^{th} 2022 to Jan 17^{th} 2023). We instrument *Platform Exposure*$_i$ with $\mathbb{1}\{Promotion\}_i$ which is a dummy variable set to 1 during the treatment only for users randomly assigned to receive the service promotion. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	D(Stock Market Participation)		ΔEquity Holding Ratio
	(1)	(2)	(3)
$PlatformExposure_i$	0.153	0.052***	2.386***
	(0.61)	(7.89)	(6.87)
Sample	SMP before the treatment	No SMP before the treatment	No SMP before the treatment
Obs	451	179,735	179,735

Table A5: Robustness I (Different Measure): Second Stage - Effect of Platform Exposure (Intensive) on Investment Behaviors

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample excluding those who have participated in the stock market before the treatment month:

$$Y_i = \alpha + \beta \widehat{PlatformExposure_i} + \varepsilon_i$$

where Y_i represents one of the six outcomes that are measured by $outcome_{Feb17^{th}} - outcome_{Jan17^{th}}$, which is the level change from the day Feb 17^{th} 2023 (the day at the end of the treatment) to the day Jan 17^{th} 2023 (the day before the treatment): Δ*Fund Balance*, the level change in the mutual fund balance of user i from the day at the end of the treatment to the day right before the treatment; Δ*Fund Number*, the level change in the number of funds held by user i from the day at the end of the treatment to the day right before the treatment; Δ*Fund Type*, the level change in the number of distinct fund types held by user i from the day at the end of the treatment to the day right before the treatment; Δ*Allocation score* and Δ*Automatic Investment Score*, the level change in the capability of allocating portfolios and the degree of automatic investment by user i from the day at the end of the treatment to the day right before the treatment; Δ*Fund Holding Duration*, the level change in the maturity of holding funds by user i from the day at the end of the treatment to the day right before the treatment. We instrument *Platform Exposure*$_i$ with $\mathbb{1}\{Promotion\}_i$ which is a dummy variable set to 1 during the treatment only for users randomly assigned to receive the service promotion. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	ΔFund Balance	ΔFund Number	ΔFund Type	ΔAutomatic Investment	ΔAllocation Score	ΔFund Holding Duration
	(1)	(2)	(3)	(4)	(5)	(6)
Platform Exposure$_i$	495.337***	0.331***	0.085***	0.373***	25.942***	0.253
	(3.90)	(8.97)	(7.42)	(5.40)	(10.54)	(0.57)
Obs	179,735	179,735	179,735	179,735	179,735	179,735

Table A6: Robustness II (*Platform Exposure*$_{alternative}$) - First Stage

This table shows coefficient estimates and associated t-statistics (in parentheses) of the following regression model based on the matching sample:

$$Intensive: Platform\ Exposure_{alternative,i} = \alpha + \theta \mathbb{1}\{Promotion\}_i + \varepsilon_i$$

where *Platform Exposure*$_{alternative}$ is measured by the total number of days users engaged with the primary digital financial information channels, including the PRA, the wealth community, and its subcomponents-the forum, short videos and image-text. It represents the level of the platform exposure the user i gained in January. $\mathbb{1}\{Promotion\}_i$ is set to 1 for the users randomly assigned to receive the service promotion during the campaign. We report t-statistics based on standard errors clustered at the individual level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Platform Exposure$_{alternative,i}$
$\mathbb{1}\{Promotion\}_i$	0.036***
	(17.85)
$Adj - R^2$	0.002
Obs	180,186
Kleibergen-Paap F-stat	318.69

Table A7: Robustness II (*Platform Exposure*$_{alternative}$ Intensive) - Second Stage on Stock Market Participation

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample:

$$Y_i = \alpha + \beta \widehat{Platform\ Exposure}_{alternative,i} + \varepsilon_i$$

where Y_i represents one of the two outcomes: *D(Stock Market Participation)*, a dummy equals to 1 if user i has ever participated in the stock market during the treatment (January campaign starting on Jan 18^{th}), and Δ *Equity Holding Ratio* measures the change in the share of equity held by user i before and during the treatment. It is computed by using the monthly average equity holding ratio from Jan 18^{th} to Feb 17^{th}, 2023 (during the treatment) to subtract the monthly average equity holding ratio from Dec 18^{th} 2022 to Jan 17^{th} 2023 (before the treatment). Column (1) and (2) show the impact of the platform exposure on *D(Stock Market Participation)* for those who have participated in the stock market in one month before the treatment (Dec 18^{th} 2022 to Jan 17^{th} 2023) and those who have not participated before, respectively. Column (3) shows the impact of the platform exposure on Δ *Equity Holding Ratio* for the treated and matched control users excluding those who have participated in the stock market in one month before the treatment (Dec 18^{th} 2022 to Jan 17^{th} 2023). We instrument *Platform Exposure*$_{alternative,i}$ with $\mathbb{1}\{Promotion\}_i$ which is a dummy variable set to 1 during the treatment only for users randomly assigned to receive the service promotion. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	D(Stock Market Participation)		ΔEquity Holding Ratio
	(1)	(2)	(3)
Platform Exposure$_{alternative,i}$	-0.013	0.046***	1.332***
	(-0.07)	(11.03)	(7.33)
Sample	SMP before the treatment	No SMP before the treatment	No SMP before the treatment
Obs	451	179,735	179,735

Table A8: Robustness II (*Platform Exposure*$_{alternative}$ Intensive) - Second Stage on Investment Behaviors

This table shows the coefficient estimates and associated t-statistics (in parentheses) of the following second-stage regression model based on the matching sample excluding those who have participated in the stock market before the treatment month:

$$Y_i = \alpha + \beta \widehat{Platform\ Exposure}_{alternative,i} + \varepsilon_i$$

where Y_i represents one of the six outcomes that are measured by the monthly average level change from the month before (Dec 18^{th} 2022-Jan 17^{th} 2023) to the month during the treatment (Jan 18^{th}-Feb 17^{th} 2023): Δ*Fund Balance*, the monthly average change in the mutual fund balance of user i from the month before the treatment to the month during the treatment; Δ*Fund Number*, the monthly average change in the number of funds held by user i from the month before the treatment to the month during the treatment; Δ*Fund Type*, the monthly average change in the number of distinct fund types held by user i from the month before the treatment to the month during the treatment; Δ*Allocation score* and Δ*Automatic Investment Score*, the monthly average change in the capability of allocating portfolios and the degree of automatic investment by user i from the month before the treatment to the month during the treatment; Δ*Fund Holding Duration*, the monthly average change in the maturity of holding funds by user i from the month before the treatment to the month during the treatment. We instrument *Platform Exposure*$_{alternative,i}$ with $\mathbb{1}\{Promotion\}_i$ which is a dummy variable set to 1 during the treatment only for users randomly assigned to receive the service promotion. We report t-statistics based on standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	ΔFund Balance	ΔFund Number	ΔFund Type	ΔAutomatic Investment	ΔAllocation Score	ΔFund Holding Duration
	(1)	(2)	(3)	(4)	(5)	(6)
Platform Exposure	317.641***	0.202***	0.041***	0.272***	18.512***	0.570*
$_{alternative,i}$	(3.77)	(9.89)	(6.40)	(5.82)	(16.18)	(1.70)
Obs	179,735	179,735	179,735	179,735	179,735	179,735