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

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**Abstract**

This paper examines the impact of a digital platform's transmission of financial knowledge on users' stock market participation and investment performance. Leveraging a Chinese platform's randomly distributed prompts as an instrument, we demonstrate that access to financial information increases stock investment, enhances portfolio diversification, and improves risk-adjusted returns, even among older, less educated, and less affluent users. Although initial responses to the prompts are modest, sustained exposure overcomes inertia and drives considerable engagement. Digitalization thus holds promises for democratizing finance by providing scalable, low-cost financial education that helps individuals make more informed investment decisions.

**Key Words:** Digital Technology Adoption, FinTech, Portfolio Choice, Individual Investors, Financial Literacy

**JEL Classification:** D14, G11, O33, Q55, G53

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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 (Berg et al., 2022; Buchak et al., 2018), and payment services (Dubey and Purnanandam, 2023; Higgins, 2020). The transformation has expanded financial inclusion by reducing transaction costs (S. Agarwal et al., 2020; Ayyagari et al., 2025; Vissing-Jørgensen, 2002) and enabling unbanked individuals to access financial services (Babina et al., 2024; He et al., 2023). Hvide et al. (2024), using data from Norway, demonstrate that increased internet usage enhances stock market participation and improves individual investors' financial decision-making. Additionally, digital technology has broadened access to financial information, a key determinant of investors' behaviors and outcomes (Ivković et al., 2008; Sialm and Xu, 2023). Social media, for instance, provides free access to financial knowledge, which influences the decisions of retail investors (Chen et al., 2025; Cookson et al., 2024; Farrell et al., 2022). Robo-advisors further empower less affluent investors, improving diversification and risk-adjusted returns (Reher and Sokolinski, 2024; Rossi and Utkus, 2024; Sialm et al., 2025).

However, households' direct investment in capital markets remains limited, even in advanced economies (Campbell, 2006; Haliassos and Bertaut, 1995; Panizza, 2015). Stock market participation rates are exceptionally low in developing countries and even advanced Asian economies, at 15%, 7%, and 6% in Japan, China, and India, respectively.[1] Paradoxically, mobile devices have high penetration rates in all of these locations, indicating that access to technology alone is insufficient to bridge the participation gap.

This paradox highlights that while mobile technology reduces traditional financial barriers, such as transaction costs and minimum investment thresholds, they do not

[1]Source: Report of How Many People Are Investing in the Markets? by MISHRA, A. (https://www.swastika.co.in/blog/population-participating-in-stock-markets-by-country).

directly address users' psychological and knowledge gaps. Behavioral inertia and limited financial literacy remain key barriers to capital market participation, particularly among older, less educated, and less wealthy individuals (Calvet et al., 2009; Lusardi and Mitchell, 2014; Madrian and Shea, 2001; Merkoulova and Veld, 2022; Thaler, 2015). Moreover, digitalization may exacerbate behavioral biases, especially among users with low financial literacy. 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. The concern is that digitalization grants access to financial services regardless of financial literacy, yet only 33% of adults worldwide are financially literate (S&P Global FinLit Survey).

Digital platforms can help overcome behavioral inertia and close knowledge gaps by using mobile technology to nudge users toward accessible, diversified investments while simultaneously delivering financial education through integrated information channels. By linking financial institutions, asset managers, and clients, these platforms provide timely, scalable, and low-cost educational content. Compared to traditional financial education programs, they offer broad, unrestricted access across user demographics, time, and location at a fraction of the cost (Kaiser et al., 2022). However, empirical research on how such approaches influence individuals' participation in stock-related market products and their investment performance is scarce.

Therefore, this paper's research question is whether and how digital nudging and transmission of financial literacy on a digital platform lead uninvolved and inexperienced households to invest meaningfully in the stock market.

China provides an interesting context for our study. In 2022, approximately 14% of the population (around 200 million individuals) invested directly in the stock market, [2] holding 20% of the total shares (Jones et al., 2023; Tan et al., 2024). The participation rate is lower among households with middle- and lower-income levels. Equity investment

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

represents only a small fraction of total household assets (less than 2%).[3] The 2019 survey data show that Chinese households tend to concentrate their wealth on real 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.[4] Moreover, recent evidence from both India and China highlights speculative trading patterns among retail investors, including poor portfolio diversification and negative long-term excess returns (V. Agarwal et al., 2025; Ayyagari et al., 2025; Jones et al., 2023). These findings suggest that even when retail investors participate in equity markets, their investment strategies and sophistication often fail to support long-term wealth accumulation, reinforcing the importance of financial knowledge in shaping household portfolio choices. However, private banking services and personal financial advisors that help reduce informational barriers are typically accessible only to individuals with substantial wealth, limiting their relevance for broader participation in the capital market.

We conduct our study using one of China's largest online investment platforms, which caters to over 1 billion customers, including 711 million monthly active users as of June 30, 2020, covering a vast geographic scope and financial statuses. We focus on the platform's capital market products, which comprise six types of mutual funds: equity, bond, hybrid, index, QDII, and gold. As of December 2022, only approximately 5% of billion platform users maintained a balance of these products exceeding CNY 100 (roughly US$14 USD) (Figure 1, Panel A). The majority of platform users exhibited minimal engagement, with 14% holding investments between CNY 0 and 100, and 81% not investing in mutual funds at all. Furthermore, non-investing platform users are disproportionately older with fewer

[3] 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.

[4] 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.

educational qualifications (no college degree), and fewer investible assets (less than CNY 50,000) (Figure 1, Panel B to D). 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.

The platform offers free access to an AI-powered personalized robo-advisory (PRA) services and an integrated wealth community for acquiring financial information and knowledge. The PRA delivers tailored investment advice, while the wealth community connects users with financial institutions, asset managers, and experts, offering real-time market insights and services. Key features include a Wealth Forum for user discussions on financial markets and products, a Super-Topic section covering current issues and trends, and columns authored by advisors. All short-video and image-based materials are classified as "Visual Content."

This study measures users' platform exposure-their interaction time, measured in seconds - with these AI-driven information channels to assess their acquisition of financial knowledge and information via the platform. We standardize the variable, scaling each observation by the maximum observed interaction time during the treatment period.

We obtain from the platform variables that measure a user's capital market investment decisions from various perspectives, such as stock market participation (defined as individuals who have made any investment that includes equity exposure), portfolio's equity holding ratio, portfolio diversification (measured by allocation score based on a metric that rises with the variety of investment product acquired), automatic investment score, fund number, fund type, fund balance and fund holding duration.[5] These detailed measures enable us to investigate the impact of access and exposure to AI-digital information transmission channels via the platform on households' detailed investment transmission channels via the platform on households' detailed investment behaviors and the resultant performance.

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

A user's platform exposure and investment decisions are endogenous. To address this, we leverage the platform's monthly "Wealth Festival" marketing campaign, which promotes its information services through randomized digital nudges sent on the 18th of each month to encourage engagement with the platform's digital information channels. We utilize the January 18, 2023 campaign to create a quasi-experimental setting. Our sample comprises approximately 0.55 million monthly active non-investing users: those aged 18 or above with a valid risk level, who logged in between December 18, 2022, and Jan 18, 2023, and had no prior platform nudges as well as exposure since the start of 2021.[6] Users in the treatment group received campaign messages, while the control group did not. We define *Nudge* as a dummy equal to 1 for participants who received these messages and use it as an instrumental variable for platform exposure in our baseline model. We randomly select a subgroup of users who did not receive the campaign messages to serve as the control group, matching the treatment group in size. After confirming that the two groups share the same distributional characteristics, we use Coarsened Exact Matching (CEM) to screen the samples further, thereby mitigating endogeneity. The final sample comprises 62,293 users in each group. Figure 2 shows the campaign timeline and the quasi-experimental design.

We provide empirical evidence of the instrument's relevance. During the treatment period, from January 18 to February 17, 2023, 1,299 (2.1%) users in the treatment group acquired platform exposure, whereas only 34 (0.05%) users in the control group did.

We measure stock market participation using $D(\textit{Stock Market Participation})_i$, an indicator equal to 1 if individual i invested in any product with equity exposure (e.g., equity-based mutual funds) during the treatment month, and zero otherwise. Digital platform exposure instrumentalized by Nudge during the treatment period significantly increased the likelihood of participation among treated users: one-unit increase in exposure raised the likelihood by 2.5%. Because users in both groups had no prior stock

[6] Non-investing users are defined as individuals with no history of investment activity on the platform, including fixed-term deposits, mutual funds (six types), or equities.

market engagement, this effect represents a substantial behavioral shift, underscoring the potential of digital financial education to reduce barriers for historically low-participation groups. Platform exposure also corresponded to a notable rise in the equity share of a user's portfolio during the treatment month.

We also investigate whether platform exposure gained during the campaign improved investment behaviors and performance. 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 their monthly average value during the treatment month ($\bar{Y}_{Jan18-Feb17,2023}$). Our results reveal that the instrumentalized platform exposure during the treatment period has a significantly positive effect on all measures of investment behavior, except for fund holding duration. This limited impact on holding duration is likely driven by the short measurement window and the fact that treated users lacked prior investment experience.

We measure users' risk-adjusted investment performance by the annualized abnormal Sharpe ratio over the 1-, 3-, and 6-month periods following the treatment. The annualized abnormal Sharpe ratio is defined as 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. Our results reveal that the instrumentalized platform exposure significantly increases the abnormal Sharpe ratio across the 1-, 3-, and 6-month horizons for the treated group compared to the control group. These results demonstrate that platform exposure has a positive, long-lasting effect on users' risk-adjusted return performance.

To understand the economic effects of platform exposure beyond statistical significance, we compare the investment behavior of individuals who engaged with financial services after receiving nudging messages with that of those in the control group during the treatment month. The former group shows an average increase in mutual fund balances of approximately CNY416 (US$58). We also find that the former group shows an increase in the variety of fund types and the portfolio allocation, highlighting enhanced portfolio diversification. The control group maintains an almost zero balance in mutual funds.

We further examine the heterogeneous effects of 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 and highly educated, and less wealthy individuals are more likely than others to acquire financial information from the platform. Platform exposure affects demographic groups differently, reflecting its ability to meet diverse investor needs. For younger, less experienced investors, it enhances capital market participation by promoting automatic investment plans and improving portfolio diversification. For more educated individuals, who already have the capacity to invest, it increases stock market participation and and further diversifies portfolios. Notably, even older, less educated, and less wealthy individuals benefit from platform-based financial education, as it helps them overcome barriers to stock market entry, expand their mutual fund holdings, diversify their assets, and improve their performance. However, opportunities remain-more educated investors could be supported in deepening engagement, while younger ones may need targeted strategies to build diversification and capacity. Further research should investigate the mechanisms behind these effects to design a more tailored intervention.

The response rate to digital nudges and the transmission of financial literacy affect its effectiveness. Although the initial response rate is low, it increases to 28.9% after six months of repeated nudging. A similar upward trend is observed across all demographic groups, including the older and less educated individuals, who are more susceptible to behavioral inertia. To measure the economic impact, we track first-time respondents across cycles, noting their investment initiation, amounts, and abnormal cumulative returns. About 24% invest CNY 2,052 ($\approx$ US$288) on average, build diversified portfolios, and consistently outperform the control group in risk-adjusted returns. These significant economic effects are also evident among older, less educated, and less wealthy respondents—groups that are typically more vulnerable and face greater behavioral inertia—highlighting the power of persistent digital nudges to expand financial knowledge and broaden inclusions.

This paper makes two contributions. First, we empirically demonstrate that digital financial education and robot advisory services, combined with digital nudging, empower investors to overcome both psychological and informational barriers to stock market participation, thereby enhancing their investment behaviors and performance. This result is particularly important given the widespread lack of financial literacy globally. Second, we demonstrate that digital financial education and robot advisory services are particularly beneficial to older, less educated, and less wealthy individuals. These groups typically avoid investing in stocks due to their behavioral inertia, limited financial literacy, and vulnerability to risk in the stock market. 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 an institutional background on the platform, including data and methodology for measuring platform exposure and identification. Section 4 examines the causal impact of platform exposure on households' stock market participation, investment behaviors, and investment performance, its economic effectiveness as well as its heterogeneous effects across different investor 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 (D'Acunto et al., 2019; Reher and Sokolinski, 2024; Rossi and Utkus, 2024), saving (Gargano and Rossi, 2024), lending (Berg et al., 2022; Buchak et al., 2018; D'Acunto et al., 2022), and payment services (Higgins, 2020). Digital payments have lowered transaction costs and eased borrowing constraints, thereby increasing business sales and consumer spending (S. Agarwal et al., 2020; Dubey and Purnanandam, 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 because households can benefit from investing in financial markets by holding 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), behavioral inertia (Merkoulova and Veld, 2022), 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) highlight the role of internet access in increasing stock market participation by improving information availability. Beyond democratizing financial information, social media further influence retail investors' decisions by shaping their perceptions and behaviors (Chen et al., 2025; Cookson et al., 2024; Farrell et al., 2022). 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, 2024).

Nevertheless, financial literacy gaps warrant emphasis. Along with the rapid expansion of digitalization, individuals can access digital financial services independent of their financial literacy. Prete (2022) suggests that it could be dangerous to increase digitalized access to finance without financial literacy. Previous studies have shown that financial literacy can empower investors to 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). Servon and Kaestner (2008) find that combining technological training with e-banking makes financial literacy training more appealing to participants, particularly among those with low to moderate incomes. Yet, raising the general public's financial literacy, especially among the older, less educated, and less wealthy groups, can be a formidable task.

Behavioral inertia is another noteworthy factor that contributes to the "stock market participation (SMP) puzzle." Here, behavioral inertia refers to the tendency to avoid exploring unfamiliar opportunities passively (Thaler, 2015; Thaler and Sunstein, 2008). Digital platforms can counter this inertia by leveraging mobile technology to nudge users toward accessible and diversified investments, while providing free financial education and peer support, thereby helping potential but financially illiterate investors.

Our work aims to contribute by examining how a digital platform — designed to prompt users with no prior stock market investment to explore its free financial information service and low-barrier investment funds — can help overcome investment hesitancy and improve investment efficiency. As outlined in the Introduction, we refer to the platform's prompting message as "**Nudge**" and users' engagement with its financial knowledge content, product information, and services as "**Platform Exposure**." We track the linkage between platform exposure and household investment in equity-based funds, as well as the performance of these investments. For identification, we use the randomly distributed nudge to instrumentalize platform exposure. Our results reveal a positive causal impact of digitally disseminating financial literacy on household investment in equity-based funds and the performance of these investments.

# 3 Background, Platform Exposure, Variables, Treatment 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 after a 2012 policy that permitted technology-based platforms to distribute mutual funds independently.[7] 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.[8]

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

[8] 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.

Second, Chinese households have experienced remarkable growth in net wealth over the past two decades, with personal investable assets reaching CNY 160 trillion (US$ 23 trillion) in 2019. However, a significant portion of personal investable assets (58%) is held in cash and deposits. As of December 2022, only 5% of the platform's users (over 1 billion) participated in the stock markets by investing in mutual funds that contain equity. It would be desirable to discover efficient ways to encourage them to invest wisely in organized markets and other alternatives to bank deposits or real estate.

Platforms use digital tools to prompt potential investors to engage with their digital and even AI-driven services, both to build financial literacy and to encourage — or even guide — market participation. Our empirical goal is to identify the causal impact of such nudged exposure to the platform on individual investment behavior and performance.

Our empirical setting is based on a marketing campaign by one of China's largest online investment platforms, which served over one billion customers in 2020 across diverse financial backgrounds. The platform provides onboard investors free digital access to financial knowledge and product information through multiple channels. Its monthly "Wealth Festival," launched on the 18th of each month, promotes these services via randomly assigned pop-up messages and homepage banners. This design creates a quasi-experimental framework to address the identification challenge in linking platform exposure to investment behavior and outcomes (details are provided in Section 4.1). We analyze the January 2023 campaign (Jan 18 – Feb 17, 2023), the "treatment month," beyond which data are unavailable.

## 3.2 Platform Exposure

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

The platform's channels for delivering informational services are as follows:

**Personalized Robo-Advisor (PRA)**: The platform offers an Investment AI Assistant designed to help investors identify suitable financial products while 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 range of financial products, gain insights into market trends, and access comprehensive financial education content, along with 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 within 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 within the wealth community and offers a diverse range of financial topics, encompassing specific investment products and indexes. If users want to gain a deeper understanding of a particular product or index, they can visit the product's forum to ask real-time questions and share ideas and experiences specific to that product. This interactive environment enriches the financial knowledge base of the community and fosters learning through peer interactions and collaborative discussions.[9]

**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.

**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 analysis. 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, measured in seconds, users spent 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 $\text{Time}_i$ denotes the total amount of time user i spends with the PRA and in the wealth community; max(Total $\text{Time}_i$) and min(Total $\text{Time}_i$) represent the maximum and minimum values of the total time spent across all users in the sample, respectively. However, if an individual did not use any digitalized financial

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

services provided by the PRA and the community, we mark her $PlatformExposure_i$ as zero. $PlatformExposure_i$ is a monthly measure, and we omit the month-year subscript.

We also record the sub-components of platform exposure: user i's interaction time with PRA and the wealth community, including its three subcomponents: "Wealth Forum," "Visual Content," and "Other."

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 engagement-frequency-based and complements the time-based.

## 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 monthly average value of their investment outcomes during the treatment month. Therefore, we extract three data sets from the platform between October 18, 2022, and July 17, 2023.

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

The second dataset is a dummy indicating whether a user received digital nudging messages promoting the platform's "Personalized Robo-advisors (PRA)" and "Wealth Community." Our IV *Nudgei* equals 1 if the sum of days that user i received a nudging message during the treatment period, from January 18 to February 17, 2023, is one or greater; 0 otherwise.

The third dataset comprises monthly observations of users' investment behaviors and performance. There are seven investment outcome variables. The first is the stock market participation, *D(Stock Market Participation)*, which equals 1 if a user made any investment that includes equity exposure, and 0 otherwise. The other six investment outcome variables are *Fund Balance, Fund Number, Fund Type, Fund Holding Duration, Allocation Score*, and *Automatic Investment Score*, which measure investors' investment in capital market products, portfolio diversification, allocation, and management. The 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 A1 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, designed to simplify the investment process and mitigate 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.

## 3.4 The Quasi-Experiment, the Treated and Control Groups

Our quasi-empirical experiment, as depicted in Figure 2, is implemented on a data population (0.55 million) extracted from the platform, comprising monthly active users (i.e., users who have logged into the platform Dec 18 2022-Jan 17 2023, one month before the January 2023 campaign) above 17 of age and who have no prior platform exposure, no history of investment activity, and had not received any service nudging messages before the start of the treatment month (Jan 18 2023). More precisely, the population comprises users with zero $\textit{Platform Exposure}_i$ and $\textit{Nudge}_i$ from January 1, 2021 to Jan 17, 2023.

During the treatment month, some individuals in the extracted population received randomly distributed messages that drew their attention to the platform's informational service channels, i.e., pop-up messages and banners on the platform's main page. They form our treated group, comprising 62,974 individuals. Due to the platform's data regulations, we can only extract a portion of the population as our potential control. Therefore, we randomly select the same number of observations (62,974 users) to serve as our potential control group. We confirm that the two groups share the same distributional characteristics, thereby adding credence to the randomness in these selections.

To further mitigate endogeneity, we use Coarsened Exact Matching (CEM) to match strictly treated and non-treated users on various baseline characteristics, including age, gender, education, risk tolerance, and investable asset level (a dummy variable indicating that a user has at least CNY 50,000 to invest). The matched sample includes 62,293 treated users and an equal number of controls in a one-to-one matching framework. Figure 3 shows the parallel trends in all investment outcomes (except for Fund Holding Duration) before and after the treatment (October 18, 2022 - July 17, 2023) for both the treated and control groups.[10]

### 3.5 Summary Statistics

Table 1 shows that the distribution of demographic characteristics and previous financial status of the treated (Panel A) and non-treated users (Panel B) before matching is similar. Panel B Col.1 displays the t-test scores for the equality of means for the treated and non-treated individuals' demographic characteristics, investable asset level, and risk level before the treatment. These t-statistics are insignificant at the 10% significance level, and the distributions of these variables in the two groups are similar. The final selected treated and non-treated users, based on Coarsened Exact Matching (CEM), have similar demographic characteristics and risk levels before the treatment, as shown in Table 2. The

[10]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)

mean difference for each variable is no more than 0.1. We also test the null hypothesis of whether the means of the treated and control distributions differ. None of the t-statistics are significant at the 10% significance level. Finally, the matched sample covers 124,586 users.

Among the treated and matched sample, the average age of users is 36 years old, with 56% being male. Only 13% possess a bachelor's degree or higher, which aligns with China's overall education level. The average risk level is 0.91, with a scale of [0,5]. Regarding investable assets, only 5% of users have investable assets of CNY 50,000 ($\approx$ US$ 6,824) or more.

# 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 platform exposure on stock market participation, investment behaviors, and performance. We further evaluate the economic significance of platform exposure and examine its heterogeneous impacts across demographic groups.

## 4.1 Identification

It is tempting to run regression analyses to explain the difference in the respective changes in the treated 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. Additionally, time-invariant user characteristics, such as age, gender, and education, may simultaneously influence individuals' investment choices and their inclination to utilize 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 shifts in investment behaviors.

We address identification challenges by leveraging the platform's marketing campaign, which delivers randomized digital service prompts via pop-up messages and banners during the campaigning period (Jan 18-Feb 17, 2023). Users exposed to these materials during the treatment month have $Nudge_i$=1, as defined in Section 3.3, and are in the treated group, whereas members of the CEM matched control have $Nudge_i$=0. Both groups had zero platform exposure before the treatment period.

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

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

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

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, as defined in Eq.1; $\mathbb{1}\{PlatformExposure\}_i$ 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, investment behaviors and performance, 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 $\beta$, which measures the mean difference in investment outcomes after acquiring platform exposure — that is, after having access and exposure to the platform's digitally delivered financial knowledge and related financial market and product information.

## 4.2 Empirical Results

### 4.2.1 First Stage — instrumentalizing platform exposure

In the first stage, we measure platform exposure in both extensive and intensive margins, estimating how digital service nudging affects the likelihood of acquiring financial knowledge and the total time engaging with information channels.

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 nudging can increase the intensity of the platform exposure on average by 0.05. In column (2), we find that the instrument $IV$ service nudging coefficient $\theta$ identifies a 2.0% increase in the probability of an uninitiated user acquiring the platform exposure during the treatment period. The parameter $\theta$ is close to the mean difference in platform exposure between the treated and control groups, as measured by both extensive and intensive margins, respectively. So we effectively use the mean difference in 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-statistic associated with these first-stage regressions is very large, indicating that the dummy variable IV represents a strong instrument.

#### 4.2.2 Second Stage: Platform Exposure and Stock Market Participation

We first analyze how platform exposure affects users' participation in the stock market. The dependent variables are *D(Stock Market Participation)* and *EquityRatio*. *D(Stock Market Participation)* is a dummy variable, which equals 1 if user i made any investment with equity exposure during the treatment month, and 0 otherwise. *Equity Holding Ratio* measures the monthly average share of equity in the portfolio during the treatment month. We use Platform Exposure (intensive) as our baseline regressor in the second-stage regression and report the results for Platform Exposure (extensive) in the Appendix.

Column (1) in Table 4 displays the impact of platform exposure on *D(Stock Market Participation)* during the treatment month. We find that a one-unit increase in platform exposure is associated with a 2.5% increase in the likelihood of participating in the stock market. This effect is not only statistically significant but also economically meaningful. Given that the sample consists entirely of users who had no prior engagement in the stock market before the treatment period, this marginal increase reflects a substantial behavioral shift among previously inactive investors. This suggests that intensive platform exposure may play a crucial role in overcoming behavioral inertia among previously inactive investors by transmitting financial knowledge and prompting broader retail participation.

Column (2) shows that a unit increase in the platform exposure is associated with a 0.742% increase in a user's equity holding share within her portfolio. Considering that the average equity holding share was zero before the treatment, this estimated effect reflects not only statistical significance but also substantial economic relevance. Table A1 in the appendix shows that measuring platform exposure using the extensive margin yields a similar significant result, indicating that receiving platform exposure can increase an investor's equity holding share by 1.924% on average. Tables 4 and A1 have an important policy implication: they suggest that a platform can increase the participation of novice investors in the equity market through digital services that disseminate financial information and knowledge.

#### 4.2.3 Second Stage: Platform Exposure and Investment Behaviors

We also investigate how platform exposure (intensive margin) affects households' investment behaviors for the matched sample. The primary investment outcomes ($\bar{Y}_{Jan18-Feb17,2023}$) are the monthly average *Fund Balance, Fund Number, Fund Type, Automatic Investment Score, Allocation Score*, and *Fund Holding Duration*.

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 platform exposure is associated with an average increase in mutual fund balance of CNY 235($\approx$ US$33) from a baseline of zero. The number of holding funds and fund types also experiences significant growth, highlighting the increase in portfolio diversification. Additionally, platform exposure can improve the scores of portfolio allocation and automatic investment by 21.319 and 0.133, respectively. Compared to the pre-treatment value of zero, the observed gains in portfolio allocation and automatic investment scores are economically significant, representing 21.32% and 0.13% of the full 0–100 scale, respectively. These improvements indicate substantial progress in participants' investment sophistication and engagement.

Among these investment outcomes, the weakest effect is observed for *Fund Holding Duration*, which remains statistically insignificant during the treatment month. This lack of impact may stem from the short measurement window, which is limited to a single month, as well as the characteristics of treated users, who had no prior investment experience on the platform. Extending fund holding duration typically requires more than initial exposure; it involves a process of experiential learning, gradual confidence building, and the internalization of long-term investment strategies. Hence, for novice investors, adopting longer-term investment behaviors is a process that evolves over time, which may not be immediately observable within the brief treatment period.

The impacts of 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. This can help investors avoid the challenge of determining the right time to invest and minimize the average cost of short-term investments.

#### 4.2.4 Second Stage: Platform Exposure and Performance

We analyze the short-term effects of platform exposure on portfolio returns, focusing on 1, 3, and 6 months. To assess performance, we adopt 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. The market Sharpe ratio is computed using daily returns and volatility over the full year of 2022, annualized accordingly. For each individual, daily mutual fund portfolio returns are used to calculate excess returns over short-term deposit rates. Volatility is estimated by the standard deviation of these daily excess returns, and the Sharpe ratio is then computed as the average excess return divided by its estimated volatility. The formal expression, annualized average excess return over the standard deviation of volatility, is as in Eq.7-8 (Appendix A2). Users with no mutual fund holdings during the analysis window are assigned a Sharpe ratio of zero.

Table 6 reports results for all users. Columns (1)–(3) show that the treated group exhibits significantly higher abnormal Sharpe ratios than the control group over 1-, 3-, and 6-month horizons. During the treatment month, each unit increase in platform exposure is associated with a 0.456-unit gain in the abnormal Sharpe ratio. This effect persists: treated users outperform controls by 0.626 and 0.551 units at the 3- and 6-month marks, respectively. These results indicate that platform exposure not only boosts short-term investment performance but also supports sustained improvements in financial decision-making.

We acknowledge that the results in Table 6 are suggestive and subject to noise. First, we do not restrict control group users from receiving nudging messages after the treatment period (Jan 18–Feb 17, 2023). Users initially assigned to the control group may have been exposed to nudging messages in subsequent months, potentially attenuating the estimated treatment effect on the longer-term performance (i.e., the 3- and 6-month abnormal Sharpe ratio). Second, exposure to future campaigns is not random: users who received messages previously are more likely to be targeted again. This likelihood may depend on their response to the initial nudging, creating endogeneity between subsequent platform exposure and investment behavior. As a result, nudging is no longer a valid instrument beyond the initial treatment period.

## 4.3 Treated Respondents

We now turn to the impact of digital nudging on recipients, via acquisition of platform exposure, on stock market participation, investment behavior, and performance. The focus is on those who received and responded to the nudging messages and acquired platform exposure, whom we refer to as treated respondents.

### 4.3.1 Effect on Stock Market Participation, Diversification, and Performance

Figure 4 illustrates the impact of digital nudging on investment outcomes (capital market participation, diversification, and performance) through the digital transmission of financial knowledge across three groups: non-recipients, recipients who did not respond, and those who responded. Significant changes are observed only in the last group. In contrast, individuals who received the message but either ignored it or clicked without engaging with the financial information services behaved similarly to the control group. However, the difference between the responding and non-responding treated users could be due to self-selection. To avoid the self-selection effect, we only compare the treated respondents to those who did not receive the nudging message.

Among treated respondents, digital nudging during the treatment month results in an average increase of 2.68 points on a scale from 0 to 100 in platform exposure, equivalent to 77 seconds. They are 21.1% more likely to initiate mutual fund investments and have a 2.2% higher probability of participating in the stock market compared to their control counterparts (which have a probability of zero). Meanwhile, they increase their mutual fund holdings by CNY416 (US$58) from a near-zero baseline, accompanied by improvements in portfolio diversification and greater gains in risk-adjusted returns during the treatment month. Moreover, their improved investment performance persists over longer horizons (3 and 6 months). The treated non-respondents behaved similarly to the control, highlighting that only those who overcome behavioral inertia to gain platform exposure experience positive changes in investment outcomes.

#### 4.3.2 Response to Consecutive Digital Nudging

The initial engagement with digital nudging is modest in the first month, with only 2.1% of recipients gaining platform exposure among 62,293 recipients. However, repeated nudging has an effective cumulative result. Figure 5 shows that the response rate increases steadily with each successive monthly nudging, reaching 28.9% after six iterations. Specifically, among the 16,527 treated users who received two consecutive months of nudging messages, 1,186 responded (7.2%). Among 9,365 who received three successive months of nudging, 1,193 responded (12.7%). This upward trend continued: 1,089 out of 6,095 responded after four consecutive months (17.9%), 991 out of 4,115 after five consecutive months (24.1%), and 928 out of 3,214 after six consecutive months (28.9%).

We find that first-time respondents in each subsequent nudging month, after the initial treatment month, exhibit immediate and statistically significant improvements in capital market participation, portfolio diversification, and risk-adjusted returns. These effects are comparable in magnitude to those observed among treated respondents during the initial treatment month, relative to the control group. Moreover, performance gains for these new respondents persist over longer periods, including 3- and 6-month horizons, as shown in Table A4.

These findings demonstrate that persistent, targeted nudging can effectively overcome behavioral inertia to increase platform exposure and then sustainably improve financial decision-making.

#### 4.3.3 Economic Effect of Consecutive Nudging

We assess the economic effectiveness of the nudging programme by tracking, across nudging cycles, the proportion of first-time respondents in each cycle who initiated investments, their investment amounts, and their cumulative abnormal gains.

Table 7 Panel A reports results for all first-time respondents with any platform exposure. Column 1 reports users who received repeated nudges from month 1 to 6, conditional on no prior responses before their first month of engagement. Column 2 displays the percentage of these users who responded and gained exposure for the first time, showing a slight upward trend. Column 3 presents the percentage of first-time respondents who initiated investments in mutual funds, which fluctuates slightly around 24%. Column 4 shows that their average fund balances in the month of first response (months 1-6) are substantially higher than the near-zero balances in the control group. Finally, Columns 5-7 indicate that these investments are associated with positive abnormal annualized Sharpe ratios over the 1-,3-, and 6-month horizons. Panel B restricts the sample to those engaging for at least one minute, indicating that greater platform exposure is associated with a higher likelihood of initiating mutual fund investments, larger allocations, and higher risk-adjusted performance.

To safeguard against the possibility that extreme outliers bias the estimates, we apply winsorization at the 1%, 2.5%, and 5% levels at both tails of the monthly average fund balance distribution. The results remain robust across all levels of winsorization. All first-time respondents continue to demonstrate significantly greater mutual fund investments on average over the 6-month horizon compared to non-recipients in the control group, consistent with our baseline findings. However, the average fund balances among respondents decline noticeably after winsorization, indicating that outliers exert an upward bias on the baseline estimates.

It is also important to note that repeated nudging, administered by the platform, might be selectively implemented (i.e., not completely random), as not all treated users receive subsequent nudges. This selective targeting may lead to a downward bias in our estimates. If all treated users had received consistent monthly nudging from month 1 to month 6, the number of respondents would likely have been higher, and the aggregate level of capital market investment correspondingly larger. Given the minimal cost associated with digital nudging, we recommend that platforms consider expanding repeated nudging strategies to maximize user engagement and promote broader retail participation in financial markets, particularly in light of the persistent behavioral inertia exhibited by many users.

## 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 nudging dummy as the regressor of the second-stage regression in Eq.5. Figure 6 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), utilization of automatic investment plan, and short-term performance (1-month abnormal

Sharpe ratio). These channels also do not lead to a significant increase in fund holding duration, so we omit the corresponding figure for brevity. Finally, *Visual Content* has a significantly greater impact than all other platform exposure components. The result highlights the significant effect of visual appeal on users.

### 4.5 Heterogeneous Effects of Platform Exposure

While the above results support that digital nudging and transmission of financial knowledge and information have a positive impact on overall stock market participation and performance, the benefits may vary across subgroups 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 suffer from financial illiteracy, have fewer investable resources, and are less prepared to comprehend and manage the risks associated with investing in stocks. Additionally, research suggests that lower-income households, constrained by liquidity issues, are typically reluctant to invest in perceived risky assets, such as stocks, prioritizing immediate financial needs over long-term investment opportunities (Lusardi and Mitchell, 2014). These groups may not even pay much attention to the nudging 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 indeed increase the stock market participation and investment performance of the older individuals, those with less education, and those with fewer investable assets.

Hence, we explore the heterogeneity in the impact of platform exposure across users' characteristics by repeating the baseline regressions from Tables 3-5 across key demographic groups. Specifically, we categorized users by age (18-24, 25-49, and 50+), education level (without or with a college education), and investable assets (below or above CNY 50,000). The outcome variables include, during the treatment month, *Stock Market Participation* and the monthly average of *Equity Holding Ratio, Allocation Score, Auto-*

*matic Investment Score, Fund Number, Fund Type, Fund Balance*, and *Abnormal Sharpe ratio* during the treatment month. These variables capture three primary dimensions: investment engagement (measured by Stock Market Participation, Equity Holding Ratio, Fund Participation, and Mutual Fund Balance), 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 nudging potential investors towards digital transmission of financial knowledge and low-barrier access to stock market investment generate desirable financial inclusion, as older, less educated, and less wealthy individuals all participate more in equity investment, with greater diversification and improved risk-adjusted returns. The details are as follows.

First, Figure 7 shows that the young, more educated, and less wealthy are more likely to acquire platform exposure when nudged 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.

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. Panels A to C of Figure 8 show the impact of platform exposure on stock market participation and performance across 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 increase their capital market participation via mutual funds and exhibit substantial growth in their mutual fund balances following exposure to the platform. However, the effect on mutual fund balances among older users is relatively weaker and statistically significant only at the 10% level (5% in a one-tailed test). These findings highlight that when the digital dissemination of financial knowledge effectively reaches those traditionally less involved in risky assets and with limited investment capacity, it enables them to participate more actively in the stock market through increased mutual fund investments. Nonetheless, for individuals such as older people who may have sufficient investment capacity but are more prone to behavioral inertia, the initial impact of platform exposure appears to be more limited. This highlights the importance of designing targeted and sustained digital nudges, particularly for populations with higher behavioral barriers. Platforms and policymakers should consider repeated engagement strategies to maintain platform exposure over a longer period and foster continued participation among these groups.

Furthermore, Panel B shows that digital financial education significantly enhances portfolio allocation capabilities across all demographic groups (except for the wealthier). 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 indicates that older, less educated, and less wealthy investors experience significant improvements in investment performance, which persist over longer horizons. Conversely, their counterparts exhibit no meaningful short-term gains but attain significantly positive abnormal Sharpe ratios over three- and six-month horizons. Interestingly, although platform exposure does not lead to significantly greater investment performance immediately among younger individuals compared to older and middle-aged groups, likely due to their limited investment capacity, it does significantly increase their adoption of automatic investment plans, facilitating more streamlined decision-making and potentially lowering long-term investment costs. The same positive impact is observed in less educated and less wealthy individuals. Thus, platform exposure not only enhances the willingness of older, less educated, and less wealthy individuals to increase their capital market investment but also improves their investment capabilities by fostering better portfolio diversification and encouraging the adoption of automatic investment plans.

In summary, these results demonstrate that digital financial education, combined with low-barrier, low-cost means of investing in stocks, benefits older, less educated, and less wealthy individuals. This finding is consistent with Reher and Sokolinski (2024), who demonstrate that Robot Advising is particularly beneficial for less affluent individuals. Correspondingly, the absence of a significant effect among more affluent individuals may be attributed to their broad access to extensive financial resources, such as private banking services, personalized financial advisors, and a wide array of investment channels beyond the platform. These individuals are likely to have already been introduced to stock market participation through wealth management professionals, reducing their reliance on the platform for investment guidance. Indeed, relative to more affluent individuals, the benefited sub-groups are more likely to need financial knowledge and are vulnerable to risky asset investment.

#### 4.5.1 Economic Effectiveness: Older, Less wealthy, and Less educated

To further assess the economic impact of digital transmission of financial knowledge in the context of a low initial response rate, we focus on treated respondents in three vulnerable subgroups — older individuals (age $\geq 50$), the less educated (non-college), and the less wealthy — and compare them with users in corresponding subgroups in the control group. Figure A2 shows that digital transmission yields substantial benefits for all three groups.

Despite their substantial potential gains from platform exposure, older, less educated, and less affluent individuals are initially less likely than younger, more educated users to utilize free financial information services or participate in capital markets. However, with repeated nudging, their responsiveness follows a similarly increasing trajectory as observed in the overall treated sample (Figure A3) and converges toward that of their counterparts. These findings suggest that persistent, targeted digital nudging can be particularly effective in overcoming behavioral inertia to gain platform exposure among populations traditionally underrepresented in capital markets, thereby amplifying the inclusiveness of financial participation.

Finally, we assess the economic effectiveness of the nudging program for all older, less educated, and less wealthy respondents who, in each cycle, newly engaged with financial information services and initiated investments. We examine their investment incidence, amounts, and cumulative abnormal gains. Table A5 shows that older respondents are more likely to hold larger mutual fund balances and achieve higher risk-adjusted returns, which may reflect their greater investment capacity. Less educated and less affluent respondents exhibit economic effects comparable in magnitude to those observed for all treated first-time respondents.

# 5 Robustness Check

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

## 5.1 Other regression models

Given that the distribution of platform exposure is highly skewed and concentrated at zero (i.e., many users exhibit no platform exposure), there is a concern that estimates from the 2SLS regression may be biased due to the non-normality of the endogenous variable. To address this potential issue, we also estimate the first-stage relationship using both a Tobit model and a Poisson Pseudo-Maximum Likelihood (PPML) model, employing the nudging dummy as an instrumental variable for platform exposure. As shown in Table A6, the nudging messages significantly increase platform exposure under both the Tobit and PPML specifications. In the second stage, platform exposure estimated from either model continues to have a significant positive effect on stock market participation and investment behaviors (Table A7-A8). These results are consistent with our baseline findings and suggest that the distributional characteristics of platform exposure do not undermine the validity of our conclusions regarding its impact on investment outcomes.

## 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' interactions with platform exposure.

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

$$Platform\ Exposure_{alternative,i} = \frac{\sum_{f=1}^{F} \frac{actual\ value_{fi} - minimum\ value_f}{maximum\ value_f - minimum\ value_f}}{F} * 100 \tag{6}$$

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 Platform $\text{Exposure}_i$ as zero.

Then, we use the Platform $\text{Exposure}_{alternative,i}$ to re-estimate the impact of platform exposure on users' investment outcomes following the baseline 2SLS regressions. Tables A9-A11 present results consistent with our baseline model, indicating that the measurement method for platform exposure does not significantly alter its positive impact on investment outcomes.

# 6 Conclusions

Digital platform exposure, as used in this paper, refers to the dissemination of up-to-date financial knowledge and product information to investors through digital channels and online networks. Such exposure also serves as a bridge between product providers and the investor community. Despite digital platforms offering low-cost access to capital market products and free informational services, household participation in the stock market remains remarkably low. To address this paradox, and recognizing that easy access to risky stock investments can cause harm without proper knowledge, we examine whether nudging potential investors toward digital platform exposure can enhance household stock market participation, improve investment decisions, and ultimately boost investment performance.

By employing a quasi-experimental research design, we find that a digital platform can nudge its users towards digital platform exposure, and this has a positive effect on households' stock market participation and financial behaviors. Platform exposure increases household investment in stock-based funds over extended periods and builds up more diverse portfolios. It also enhances investors' investment performance, as evidenced by the abnormal Sharpe ratio of their investment portfolio.

This study also demonstrates that the impact of digital platform exposure varies across demographic groups. The findings reveal that while those who are younger, more educated, and less wealthy are more likely to acquire platform exposure after being nudged, the effect is remarkably 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 experience in investing in the capital market, and they are more likely to face significant behavioral and economic barriers to participating in the capital market. Therefore, the results highlight that nudging potential investors towards the digital transmission of financial information and knowledge can raise financial inclusion.

Our study addresses a key gap in both research and practice. While financial platforms increasingly offer tools such as robo-advisors, chatbots, and online courses, their actual usage and impact remain limited and not well understood. Existing nudging strategies to promote these services tend to be mild, generic, and short-lived. We find that a one-off prompt produces only modest effects, whereas sustained nudging over six months dramatically increases user responses from 2% to 29%. Moreover, newly responding recipients in each month of continued nudging showed meaningful improvements in the economic efficiency of their investments, characterized by greater diversification and sustained favorable expected return-risk performance. These results underscore the need for persistent targeted nudging to overcome behavioral inertia.

Our paper has implications for policy and financial education initiatives. Transmitting financial knowledge to stock investing via digital platforms is a low-cost, scalable, and impactful alternative to traditional approaches, facilitated by a persistent nudging program. This is particularly important given the widespread lack of financial literacy globally. Moreover, the varying impacts of financial knowledge across diverse user profiles underscore the need to tailor educational content to individual needs.

This paper represents an initial attempt to investigate the impact of learning finance through digital platforms on household investment behaviors and performance. While the results are positive and intuitively appealing, the long-term effects of platform exposure need further investigation. Additionally, there may be unexplored costs and unexpected consequences; for example, self-interested service providers can take advantage of digital platform exposure to exploit unsuspecting users. Further studies are necessary to understand the effects of platform exposure on household welfare fully.

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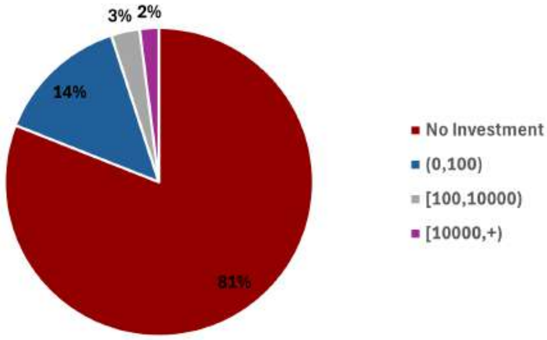
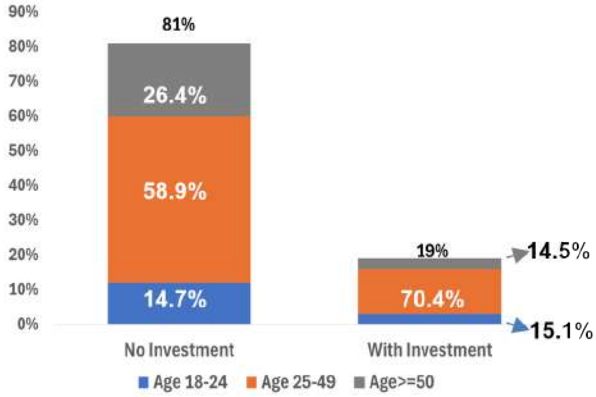
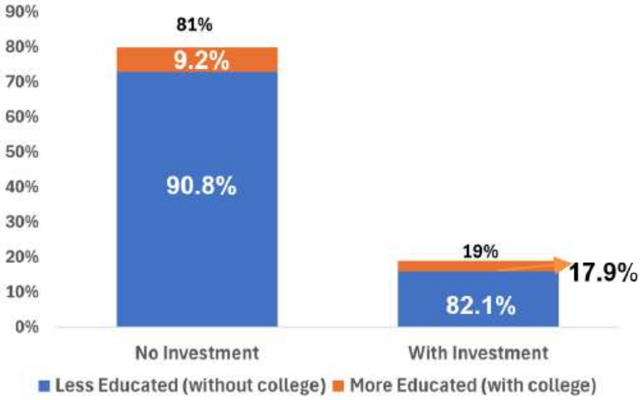


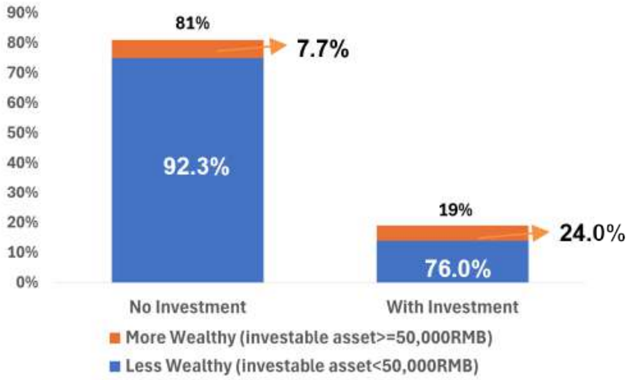

Panel A. The Overall Distribution




Panel B. By Age




Panel C. By Education Level

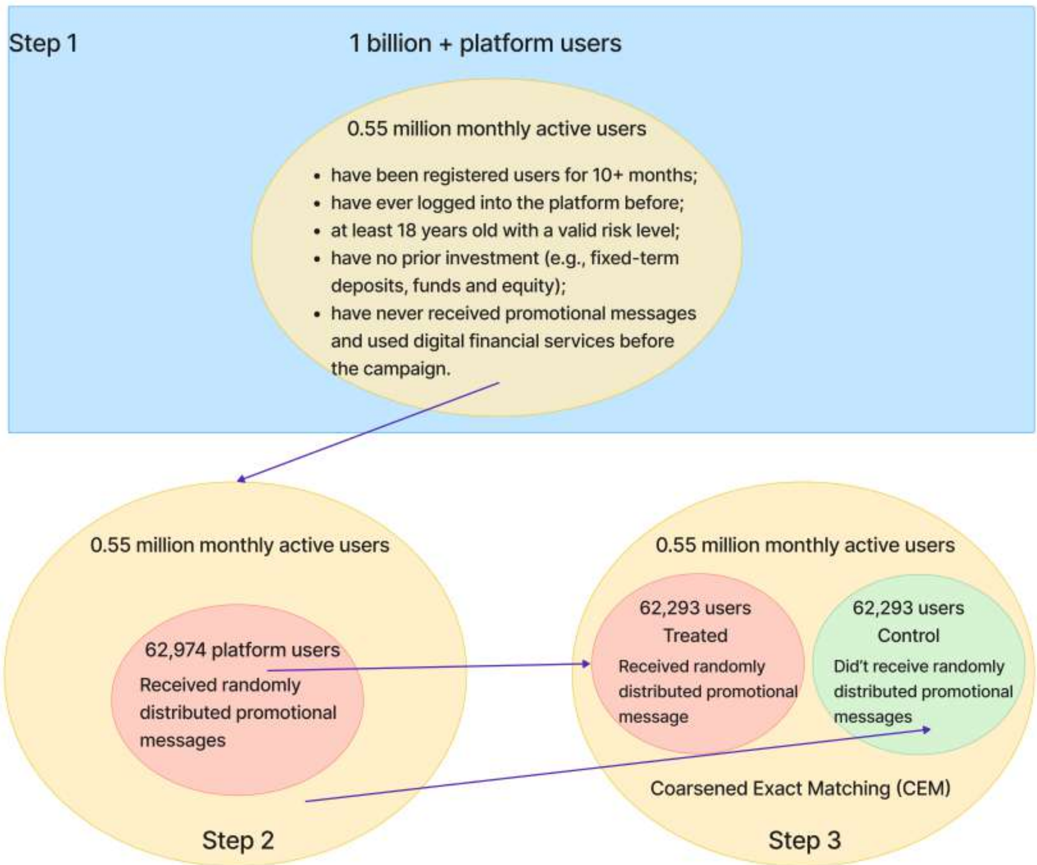



Panel D. By Investable Asset

**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) CNY (0, 100), (3) CNY [100, 10,000), and (4) CNY 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 CNY 50,000, and "Less Wealthy" have assets below this threshold. Subgroup percentages reflect their share of the total within each investment category (No Investment/With Investment). Source: Calculations are based on platform data (1 RMB = 0.14 USD).

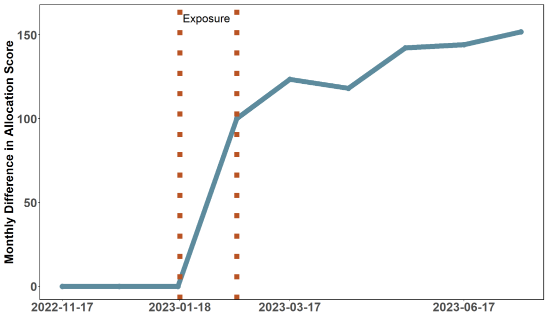

A. Timeline



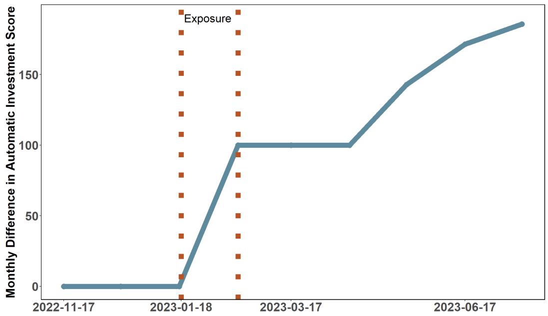

B. Quasi-experimental population & sample

**Figure 2: Quasi-Experimental Setting**

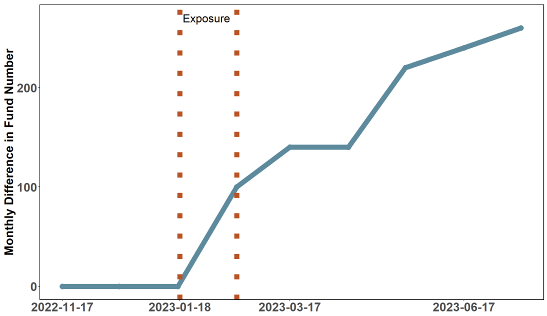
This figure displays the timeline of the marketing campaign starting on January $18^{th}$ (Panel A), as well as the quasi-experimental population and its relationship with the quasi-experimental sample.



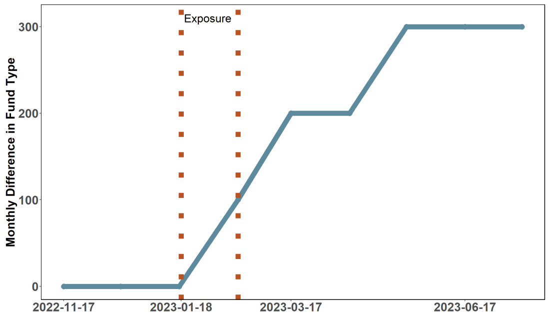

A. Allocation Score



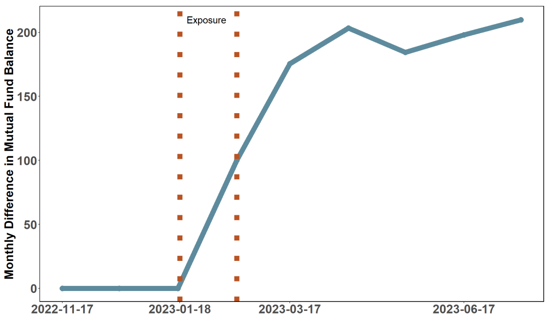

B. Automatic Investment Score



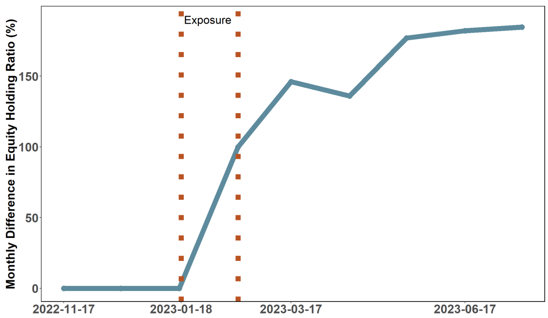

C. Fund Number




D. Fund Type



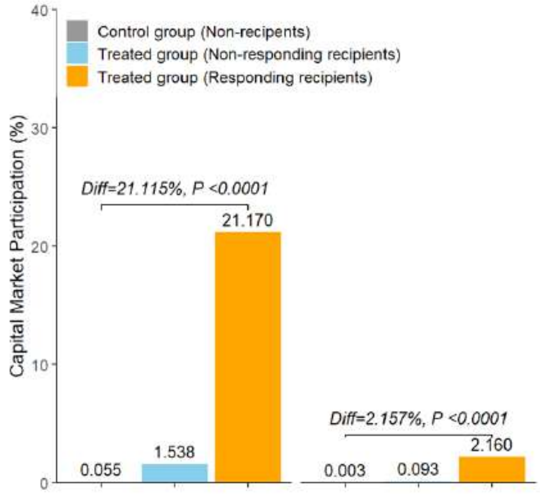

E. Fund Balance



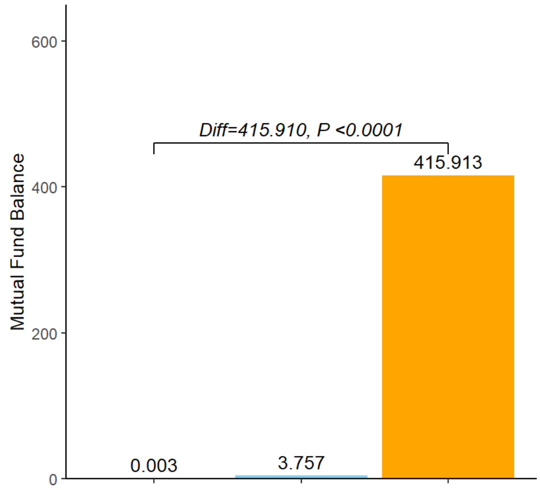

F. Equity Holding Ratio

**Figure 3: Matched Sample - Parallel Trend in Investment outcomes**

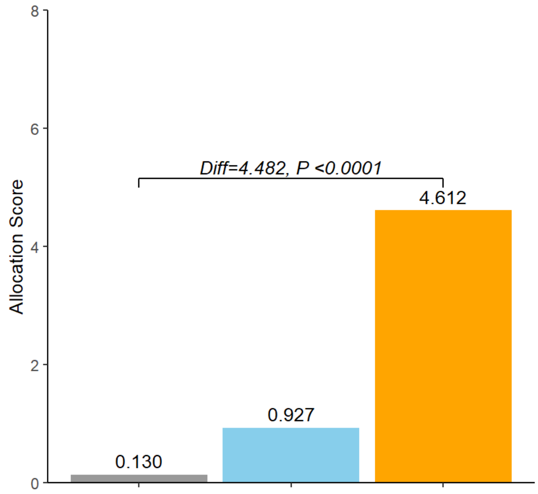
This figure illustrates the parallel trends in investment outcomes for treated users and their matched counterparts. The investment outcomes analyzed include the *Allocation Score, Automatic Investment Score, Fund Number, Fund Type, Fund Balance, and Equity Holding Ratio* (Panel A-F). The vertical axis 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.



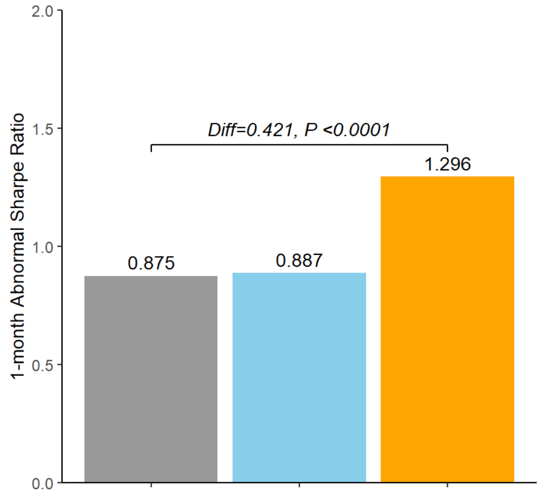

A. Capital Market Participation




B. Mutual Fund Investment



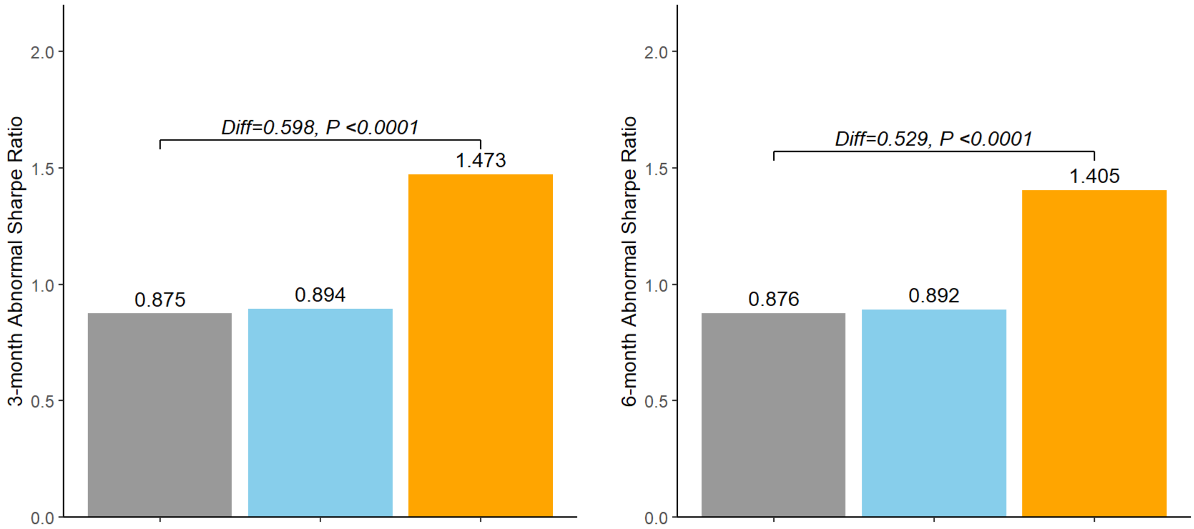

C. Allocation Score




D. 1-month Abnormal SP

**Figure 4: Impact of Platform Exposure: Treated Respondents**

This figure display the impact of digital nudging through financial knowledge dissemination on four key investment metrics: (1) capital market participation, measured using two binary indicators – (i) "stock" is defined as individuals who have made any investment that includes equity exposure (i.e., investments in equity-based mutual funds or other products containing equity components), and (ii) "mutual fund" capturing capital market participation via mutual funds), (2) mutual fund balance, (3) portfolio diversification (measured by the platform's allocation score), and (4) risk-adjusted performance (measured by the abnormal Sharpe ratio) over 1-, 3- and 6-month horizons (Panel A to F). Each bar represents one of the three groups: users in the control group (62,293 users), non-responding recipients in the treated group (60,994 users), and responding recipients in the treated group (1,299 users). "Diff" reports the difference in investment outcomes between the control group and responding recipients, along with the corresponding p-value.




E. 3-month Abnormal SP

F. 6-month Abnormal SP

**Figure 4: Impact of Platform Exposure: Treated Respondents (Continued)**

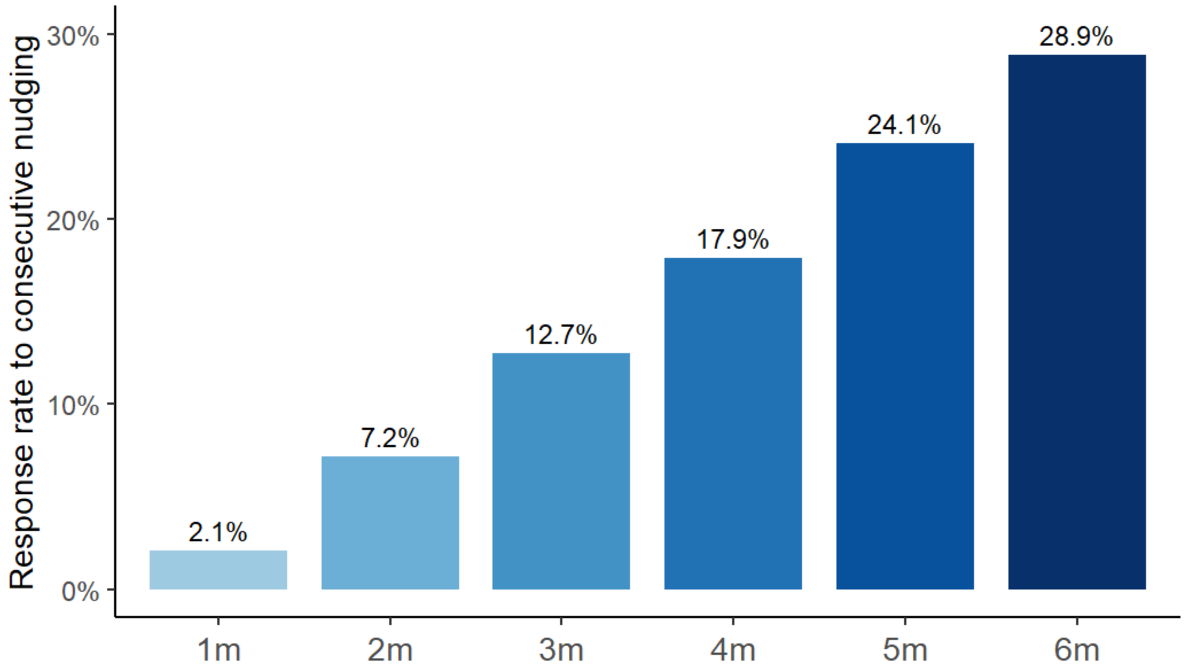
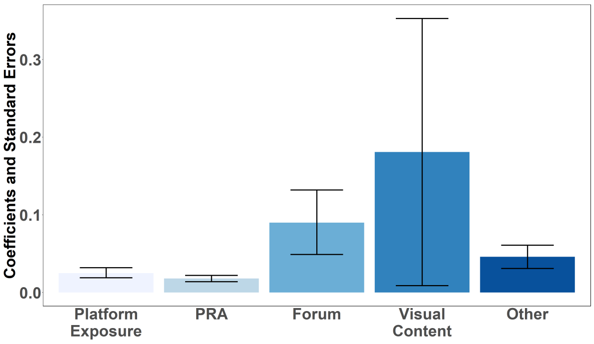
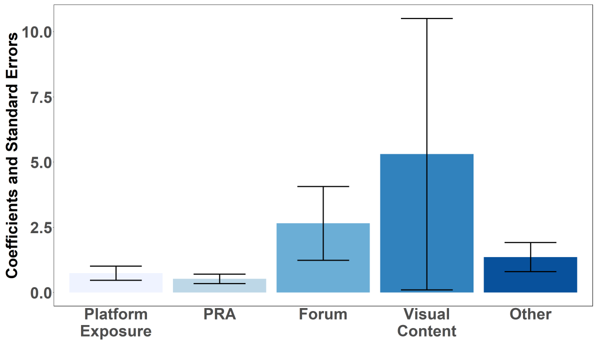



**Figure 5: Response Rates to Digital Nudging Across Repeated Nudging Horizons**

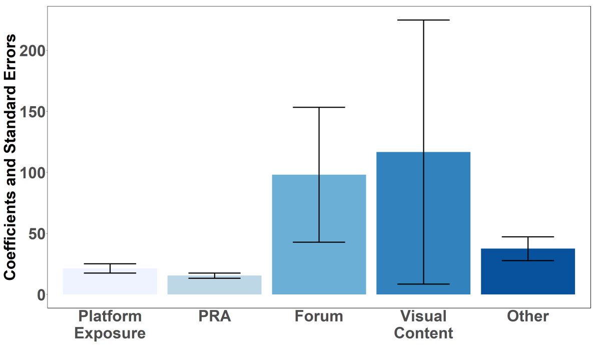
The figure shows the cumulative proportion of treated users (62,293 recipients) who ever responded to consecutive digital nudging messages over six consecutive monthly prompting cycles. The vertical axis denotes the cumulative rate of recorded responses, while the horizontal axis indicates the number of monthly nudges received. Recorded response rates cumulated steadily with consecutive digital nudging.



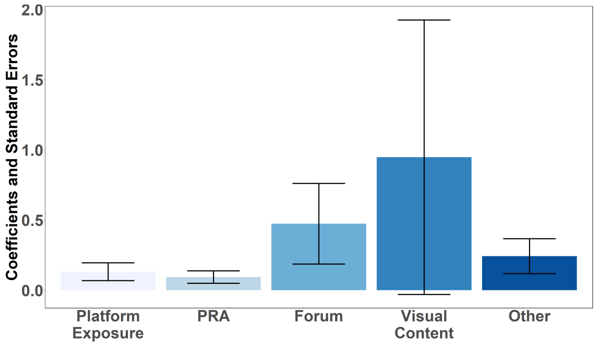

A. D(Stock Market Participation)




B. Equity Holding Ratio (%)



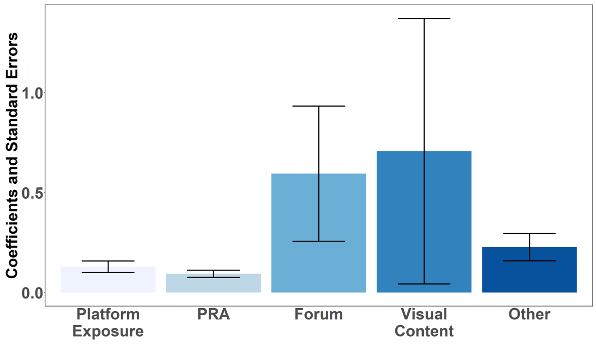

C. Allocation Score



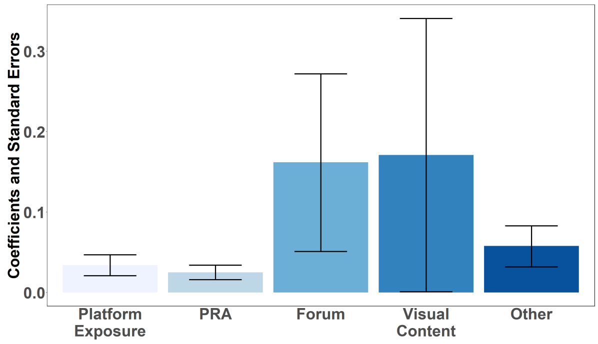

D. Automatic Investment Score

**Figure 6: Heterogeneous Impact of Platform Exposure Components on Investment Outcomes**

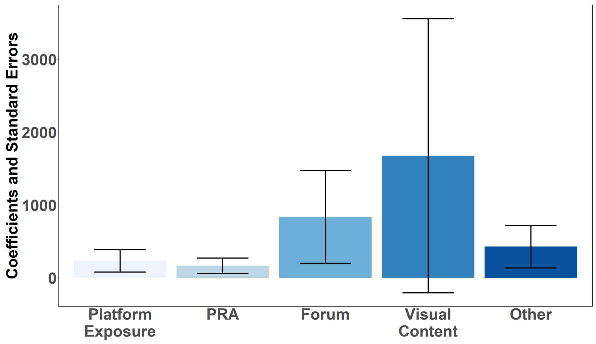
This figure illustrates the heterogeneous impact of different subcomponents of platform exposure on the investment outcomes for the matched sample. Platform exposure is categorized into Personalized Robo-Advisor (PRA) and the Wealth Community, which is further divided into three subcomponents: "Wealth 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 the monthly average value of *Stock Market Participation, Equity Holding Ratio, Allocation Score, Automatic Investment Score, Fund Number, Fund Type, Fund Balance*, and *Abnormal Sharpe ratio* during the treatment month. 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.



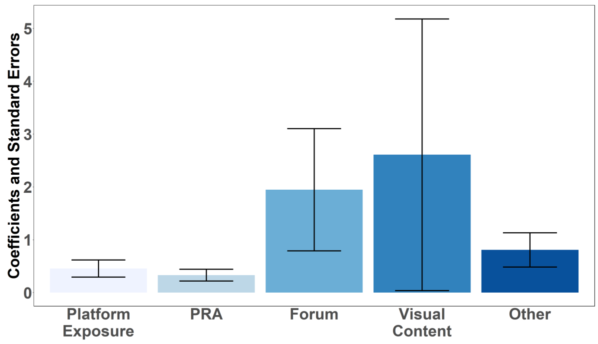

E. Fund Number



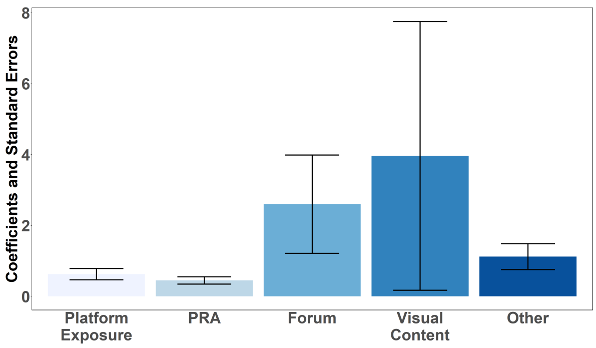

F. Fund Type



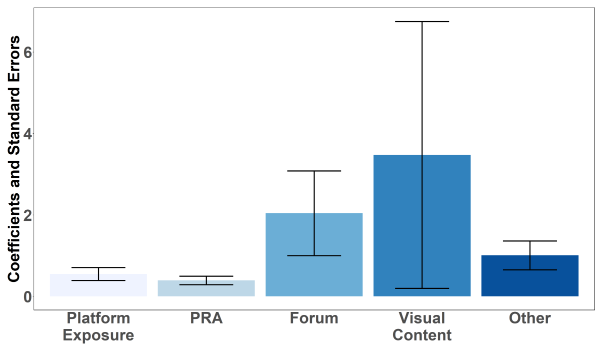

G. Fund Balance




H. 1-month Abnormal SP




I. 3-month Abnormal SP




J. 6-month Abnormal SP

**Figure 6: Heterogeneous Impact of Platform Exposure Components on Investment Outcomes (Continued)**

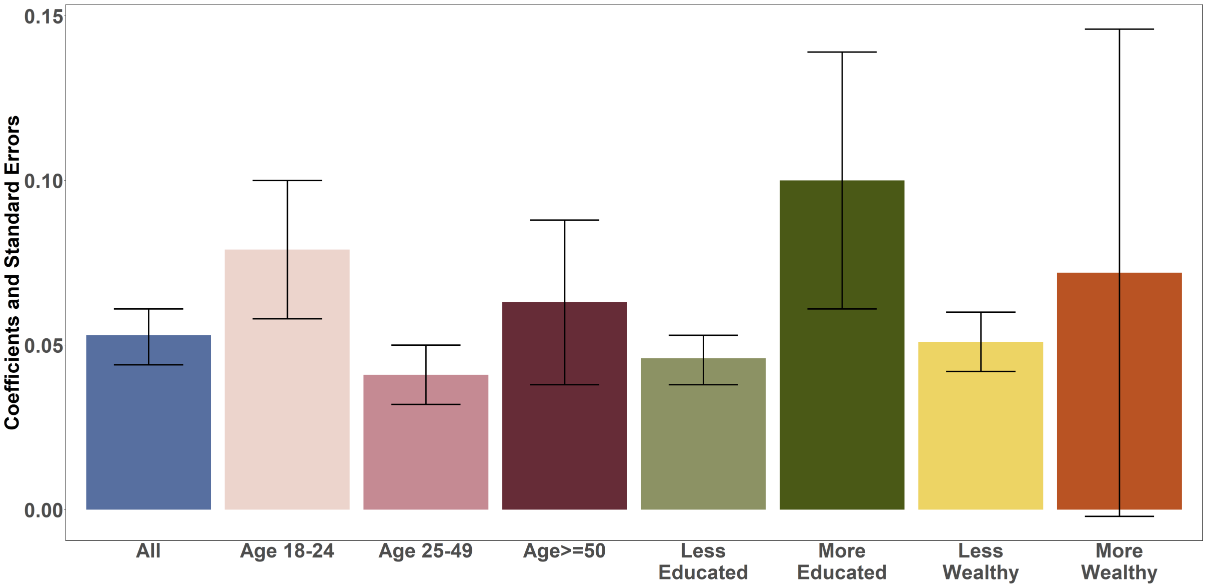
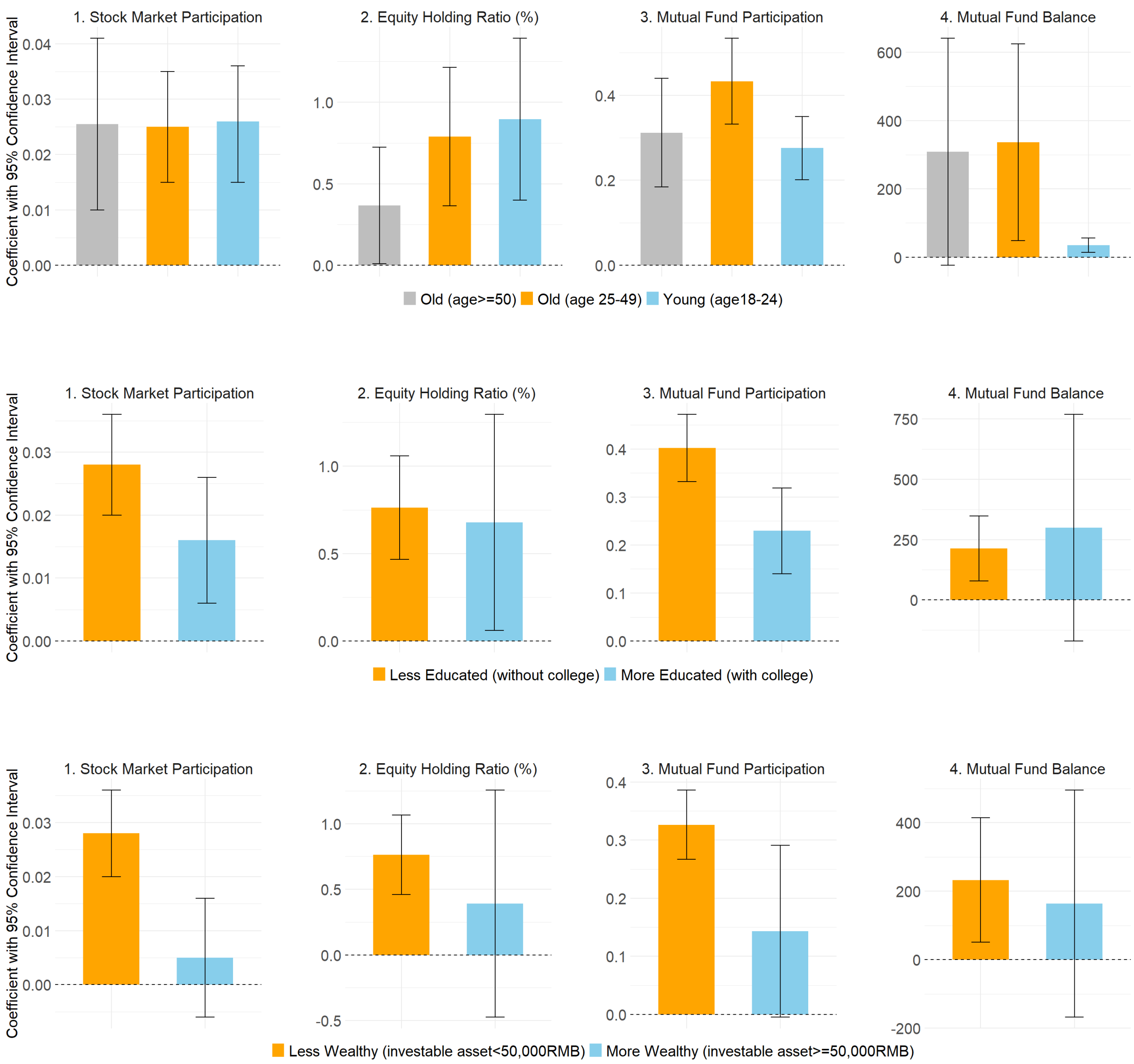



**Figure 7: Heterogeneous Platform Exposure (Intensive) Across Users' Characteristics**

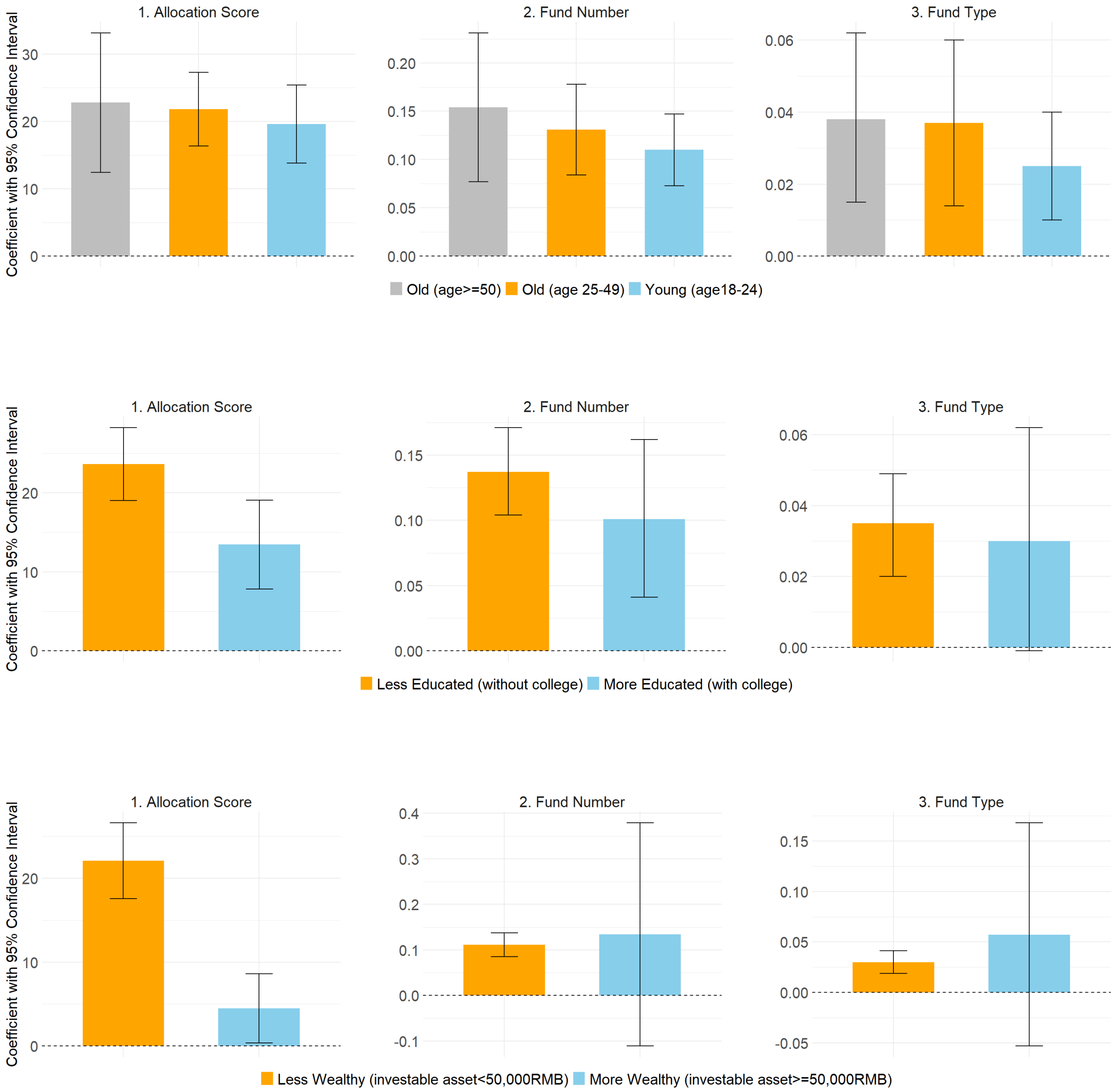
This figure reports the heterogeneous effect of service nudging on the acquisition of platform exposure across various characteristics. The vertical axis represents the coefficient estimates and associated 95% confidence intervals of the first-stage regression model: $PlatformExposure_i = \alpha + \theta \mathbb{1}\{Nudge\}_i + \varepsilon_i$. 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 CNY 50,000).




Panel A. Investment Engagement

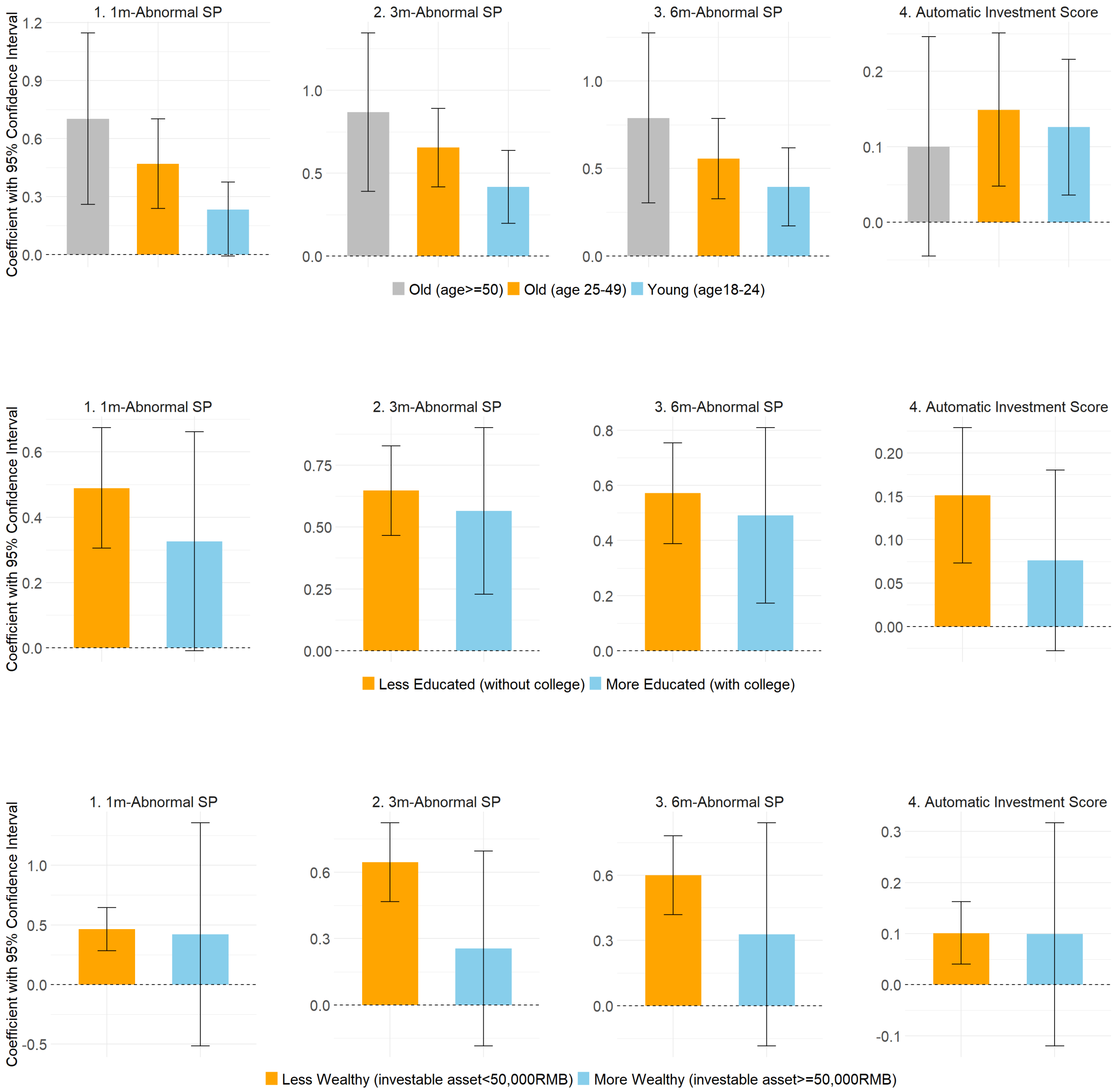
**Figure 8: Heterogeneous Impact of Platform Exposure Across Users' Characteristics**

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 Participation (Dummy), Fund Balance*; portfolio diversification (Panel B), including *Allocation Score, Fund Number, Fund Type*; and investment performance (Panel C), including *Abnormal Sharpe ratio* over 1-,3- and 6-month horizons, and *Automatic Investment Score*. The vertical axis represents the coefficient estimates and associated 95% confidence intervals of the second-stage regression model: $Y_i = \alpha + \beta \widehat{PlatformExposure_i} + \varepsilon_i$.




Panel B. Portfolio Diversification

**Figure 8: Heterogeneous Impact of Platform Exposure Across Users' Characteristics (Continued)**




Panel C. Investment Performance and Other

**Figure 8: 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 t-statistics for equality of means between the treated and matched non-treated groups, as well as summary statistics (n, mean, standard deviation, 1st, 25th, 50th, 75th, and 99th percentiles). Key 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; *Investable Asset>= CNY 5W*, a dummy for users with investable assets of CNY 50,000 (around 6,824 USD) or above; and *Risk Level* is measured by investors' answers to the platform's risk survey and represents risk tolerance, ranging from 0 to 5;

| | | N | Mean | SD | P1 | P25 | P50 | P75 | P99 |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A. Treated** | | | | | | | | | |
| Age | | 62,974 | 36.19 | 12.29 | 18 | 26 | 35 | 45 | 68 |
| Gender | | 62,974 | 0.56 | 0.50 | 0 | 0 | 1 | 1 | 1 |
| High Education | | 62,974 | 0.13 | 0.34 | 0 | 0 | 0 | 0 | 1 |
| Investable Asset>= CNY 5W | | 55,039 | 0.06 | 0.24 | 0 | 0 | 0 | 0 | 1 |
| Risk Level | | 62,974 | 0.92 | 1.17 | 0 | 0 | 0 | 2 | 4 |
| **Panel B. Non Treated (Pre Matching)** | | | | | | | | | |
| | t-test | N | Mean | SD | P1 | P25 | P50 | P75 | P99 |
| Age | -0.58 | 62,974 | 36.23 | 12.24 | 18 | 26 | 35 | 45 | 68 |
| Gender | 0.00 | 62,974 | 0.56 | 0.50 | 0 | 0 | 1 | 1 | 1 |
| High Education | 0.81 | 62,974 | 0.13 | 0.34 | 0 | 0 | 0 | 0 | 1 |
| Investable Asset> CNY 5W | 1.48 | 55,039 | 0.06 | 0.23 | 0 | 0 | 0 | 0 | 1 |
| Risk Level | 1.12 | 62,974 | 0.91 | 1.16 | 0 | 0 | 0 | 2 | 4 |

**Table 2: Matching Sample Distribution**

This table presents cross-sectional summary statistics for a matched sample of 124,586 platform users. We report the mean difference between treated and matched non-treated groups, t-statistics for equality of means, and summary statistics (n, mean, standard deviation, 1st, 25th, 50th, 75th, and 99th percentiles) for the whole matched sample. Baseline characteristics include *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), and *Investable Asset>= CNY 5W* (a dummy for investable assets greater than or equal to CNY 50,000), and *Risk Level* (measuring risk tolerance, 0-5). N is 124,586 for each variable.

| | $\overline{Diff}$ | t-stat | N | Mean | SD | P1 | P25 | P50 | P75 | P99 |
|---|---|---|---|---|---|---|---|---|---|---|
| Age | -0.04 | -0.52 | 124,586 | 36.17 | 12.26 | 18 | 26 | 35 | 45 | 68 |
| Gender | 0.00 | 0.00 | 124,586 | 0.56 | 0.50 | 0 | 0 | 1 | 1 | 1 |
| High Education | 0.00 | 0.00 | 124,586 | 0.13 | 0.34 | 0 | 0 | 0 | 0 | 1 |
| Investable Asset>= CNY 5W | 0.00 | 0.00 | 108,902 | 0.05 | 0.22 | 0 | 0 | 0 | 0 | 1 |
| Risk Level | 0.00 | 0.00 | 124,586 | 0.91 | 1.15 | 0 | 0 | 0 | 2 | 4 |

**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:

$$PlatformExposure_i = \alpha + \theta \mathbb{1}\{Nudge\}_i + \varepsilon_i$$

$$\mathbb{1}\{PlatformExposure\}_i = \alpha + \theta \mathbb{1}\{Nudge\}_i + \varepsilon_i$$

where 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. $\mathbb{1}\{Nudge\}_i$ is set to 1 for the users randomly assigned to receive the service nudging during the January campaign. Column (1) and (2) display the impact of the nudging messages on Platform Exposure$_i$ and $\mathbb{1}\{PlatformExposure\}_i$, 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.

| | $PlatformExposure_i$ | $\mathbb{1}\{PlatformExposure\}_i$ |
|---|---|---|
| | Intensive | Extensive |
| $\mathbb{1}\{Nudge\}_i$ | 0.053*** | 0.020*** |
| | (12.28) | (35.01) |
| Adj $R^2$ | 0.001 | 0.010 |
| Obs | 124,586 | 124,586 |
| Kleibergen-Paap F-stat | 150.602 | 1213.452 |

**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 *Equity Holding Ratio*, which measures the equity share held by user $i$ during the treatment. Column (1) and (2) show the impact of platform exposure on *D(Stock Market Participation)* and *Equity Holding Ratio* for treated and matched control users. Platform exposure is instrumented using $\mathbb{1}\{Nudge\}_i$ , a binary variable set to 1 for users randomly assigned to receive the service nudging 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) | Equity Holding Ratio (%) |
|---|---|---|
| | (1) | (2) |
| $Platform\quad Exposure_i$ | 0.025*** | 0.742*** |
| | (7.48) | (5.39) |
| Obs | 124,586 | 124,586 |

**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:

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

where $Y_i$ represents one of six outcomes, each measuring the monthly average value during the treatment month: *Fund Balance*, *Fund Number*, *Fund Type*, *Allocation Score*, *Automatic Investment Score*, and *Fund Holding Duration*. These variables capture the average value of mutual fund balance, number of funds, distinct fund types, portfolio allocation capability, degree of automatic investment, and fund holding duration during the treatment month, respectively. We instrument platform exposure using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the nudging messages 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. | Fund Balance | Fund Number | Fund Type | Automatic Investment | Allocation Score | Fund Holding Duration |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Platform Exposure*$_i$ | 234.567*** | 0.129*** | 0.034*** | 0.133*** | 21.319*** | 0.536 |
| | (3.00) | (8.70) | (5.06) | (4.07) | (10.98) | (1.42) |
| Obs | 124,586 | 123,686 | 123,438 | 124,586 | 123,688 | 123,340 |

**Table 6: Second Stage - Effect of Platform Exposure (Intensive) 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:

$$Y_i = \alpha + \beta Platf\widehat{ormEx}posure_i + \varepsilon_i$$

where $Y_i$ represents the investment performance, measured by the abnormal Sharpe ratio, as the difference between the investor's Sharpe ratio and the market portfolio's Sharpe ratio (SSE Composite Index). The investor's Sharpe ratio is calculated using daily mutual fund portfolio returns over 1-month (Column 1), 3-month (Column 2), and 6-month (Column 3) periods following the treatment. For users with no mutual fund holdings, the Sharpe ratio is set to zero. Column (1)-(3) report the effect of platform exposure on abnormal Sharpe ratios over the respective time horizons. *Platform exposure*$_i$ is instrumented using $\mathbb{1}\{Nudge\}_i$, a dummy set to 1 for users randomly assigned to the nudging messages 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. | Abnormal Sharpe ratio | | |
|---|---|---|---|
| | 1-month | 3-month | 6-month |
| | (1) | (2) | (3) |
| *Platform Exposure*$_i$ | 0.456*** | 0.626*** | 0.551*** |
| | (5.53) | (7.64) | (6.79) |
| Obs | 123,741 | 123,354 | 122,888 |

**Table 7: Economic Effectiveness of Repeated Nudging Among First-Time Respondents**

This table presents the proportion of first-time respondents from 62,293 recipients in the treated group, in each cycle who initiated investments, their investment amounts, and their cumulative abnormal gains. Col (1), "# recipients (no prior response)," shows the number of treated users who received repeated nudging across the first to sixth months (1m–6m) but had not responded before the month of their first response. Col (2), "#1st-time respondents (%)," lists the proportion of first-time respondents among the recipients in Col (1). Col (3), "# Invested respondents," shows the proportion of first-time respondents who subsequently invested in mutual funds. Col (4), "Average Fund Balance," displays the average monthly mutual fund balance for the month in which the first response was made. Col (5), "1-month abnormal SP", is the abnormal annualized Sharpe ratio calculated over the one month following the initial response, and as explained in Eq. 7 and 8. Cols (6) and (7), respectively, list the abnormal annualized Sharpe ratios over the three- and six-month horizons, corresponding to the month of the first response. Col (4)-(7) are based on the first-time respondents who have initiated mutual fund investments. This table focuses on capital market participation through mutual funds, excluding stock investments due to the unavailability of monetary data for the latter. Equity investment is also limited, with only 2% of first-time respondents participating, compared to 24% for mutual funds. Panel A reports results for all first-time respondents with any platform exposure, whereas Panel B restricts the sample to those engaging for at least one minute.

Panel A.1st-time Respondents (platform exposure>0)

| | # recipients (no prior response) | #1st-time respondents (%) | # Invested respondents(%) | Average Fund Balance | 1-month abnormal SP | 3-month abnormal SP | 6-month abnormal SP |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| 1m | 62,293 | 2.09% | 21% | 1,965 | 4.72 | 4.79 | 3.72 |
| 2m | 15,760 | 2.66% | 26% | 1,546 | 3.04 | 4.27 | 3.56 |
| 3m | 8,443 | 3.21% | 29% | 252 | 7.32 | 3.44 | 1.93 |
| 4m | 5,154 | 2.87% | 31% | 7,896 | 4.59 | 4.51 | 3.66 |
| 5m | 3,226 | 3.16% | 32% | 179 | 5.69 | 4.19 | 4.47 |
| 6m | 2,363 | 3.26% | 22% | 2,956 | 5.77 | 2.97 | 3.25 |

Panel B.1st-time Respondents (platform exposure>60 seconds)

| | # recipients (no prior response) | #1st-time respondents (%) | # Invested respondents(%) | Average Fund Balance | 1-month abnormal SP | 3-month abnormal SP | 6-month abnormal SP |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| 1m | 62,293 | 0.60% | 30.46% | 3,438 | 5.62 | 5.14 | 4.31 |
| 2m | 16,279 | 0.98% | 31.88% | 1,062 | 4.69 | 7.2 | 5.90 |
| 3m | 9,035 | 1.07% | 42.27% | 778 | 7.09 | 4.2 | 2.31 |
| 4m | 5,739 | 0.89% | 43.14% | 14,446 | 1.75 | 1.59 | 0.46 |
| 5m | 3,770 | 1.25% | 31.91% | 1,599 | 9.23 | 7.53 | 6.59 |
| 6m | 2,867 | 1.60% | 19.57% | 6,938 | 7.25 | 6.70 | 5.41 |

# 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 Measurement of Investment Performance

To assess risk-adjusted performance, we use the annualized abnormal Sharpe ratio and compute it following the steps:

1) using an individual's daily mutual fund portfolio return over a 1-month (or 3- and 6-month) period following the treatment to calculate the daily volatility;

2) Calculating the annualized Sharpe ratio of an individual's portfolio and the market portfolio (SSE Composite index) following the equation 7:

$$\text{Sharpe ratio}_{annualized} = \frac{(\overline{daily \quad return} - daily \quad deposit \quad rate) * \sqrt{252})}{\sqrt{daily \quad volatility}} \tag{7}$$

where $\overline{daily \quad return}$ is the mean value of the daily portfolio return over a 1-month (or 3- and 6-month) period following the treatment, and the daily volatility is the variation of the daily return over the respective horizon, computed in the step (1). The daily deposit rate is the daily demand deposit interest rate offered by China's commercial banks. Users with no mutual fund holdings during the analysis window are assigned a Sharpe ratio of zero.

3) Generating the abnormal Sharpe ratio following Equation 8:

$$\text{Abnormal Sharpe ratio}_{annualized} = \text{Sharpe ratio}_{annualized,useri} - \text{Sharpe ratio}_{annualized,marketportfolio} \tag{8}$$

where the annualized Sharpe ratio of the market portfolio is computed following Eq. 7 using the full year of 2022 data.

## A.3 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 by making any investment that contains equity (i.e., equity-based mutual fund), as depicted in Figure A1. Although Shanghai (China's largest city and a global financial hub) has the highest stock market participation rate of 10.4% through the platform we analyzed, this figure remains substantially lower than the corresponding rate in 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 more accessible and affordable, the digital transmission of financial knowledge could thus be instrumental in raising households' stock market participation.

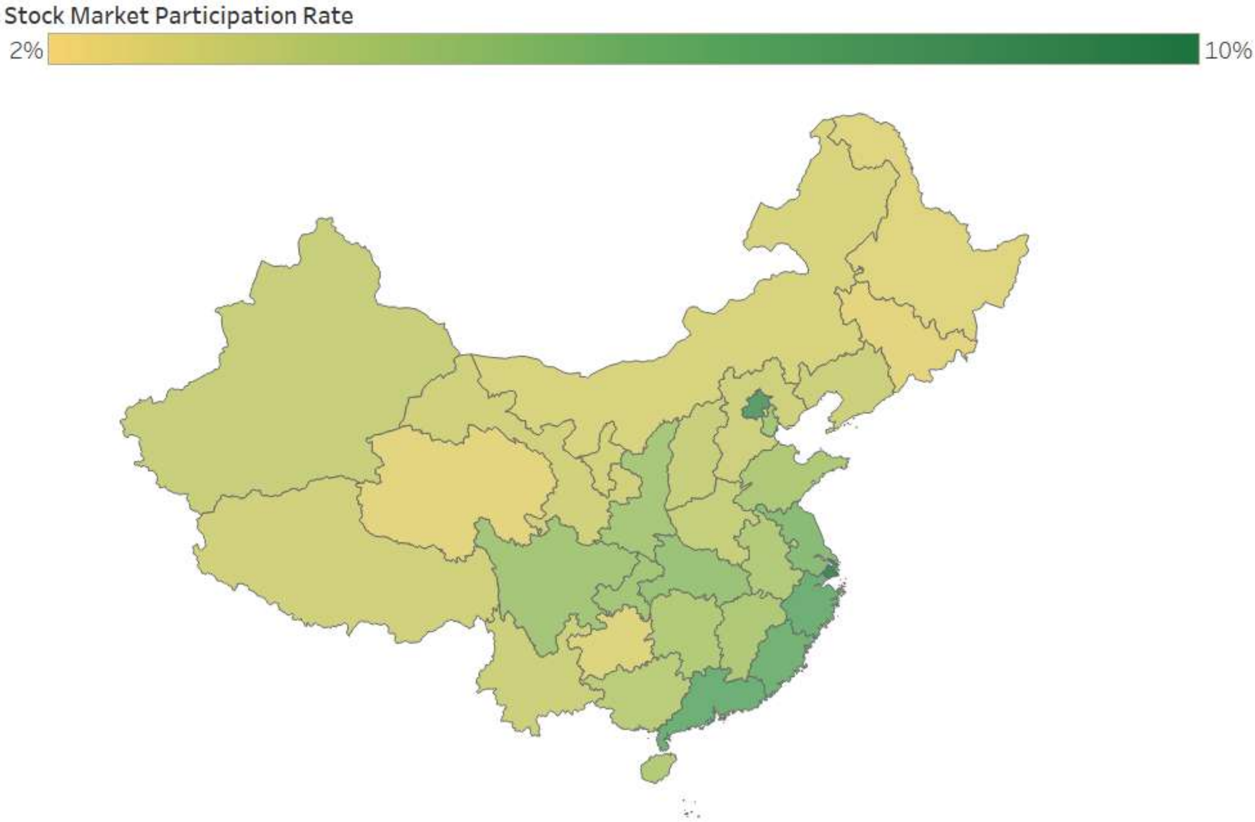
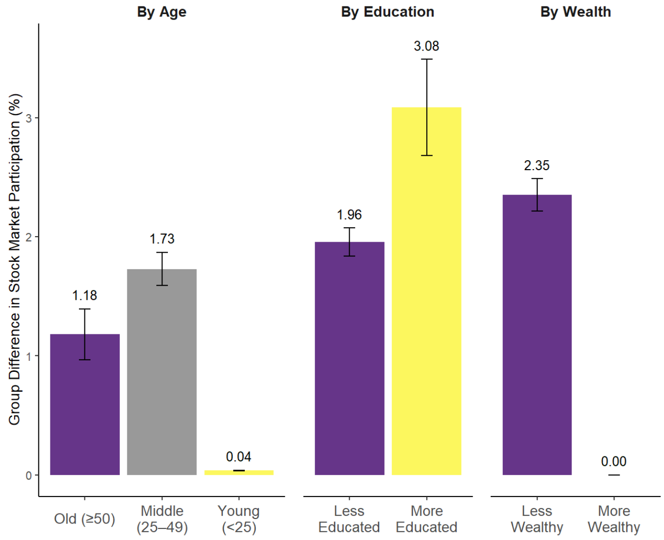
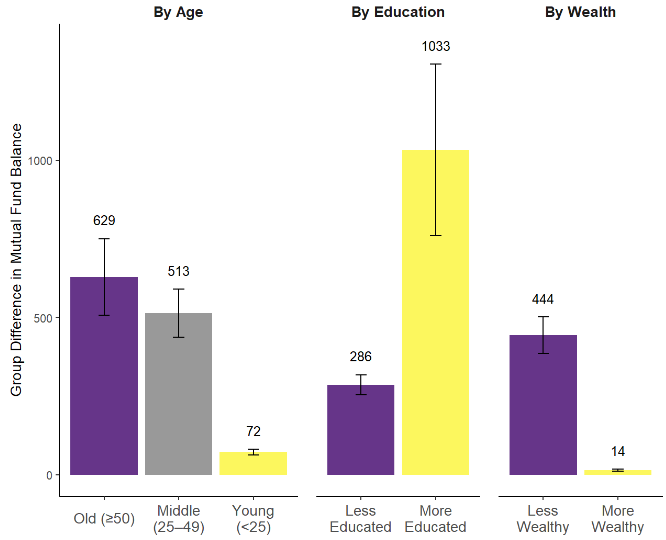



**Figure A1: Stock Market Participation Rate of Platform Users**

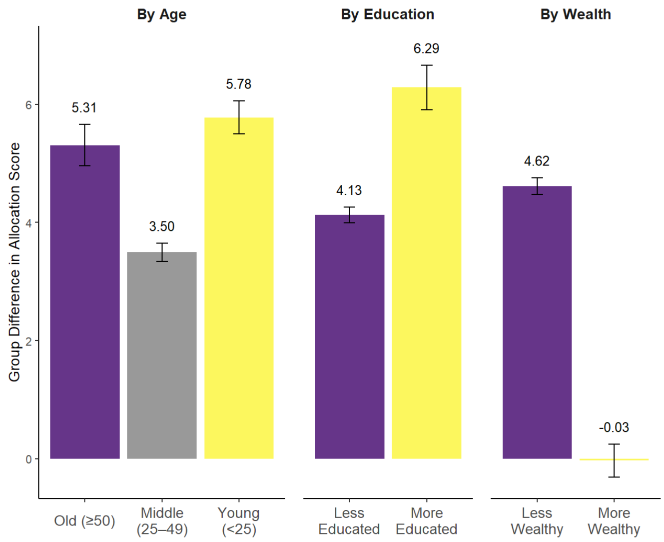
This figure shows the percentage of all platform users who participate in the Chinese stock market by making equity-exposed investments through the platform at the beginning of December 2022. Source: All calculations are based on data obtained from the platform we analyzed.



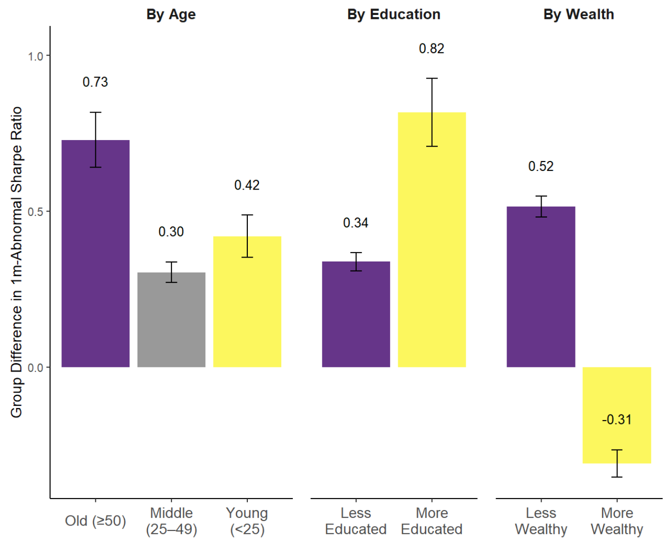

A. Stock Market Participation




B. Mutual Fund Investment



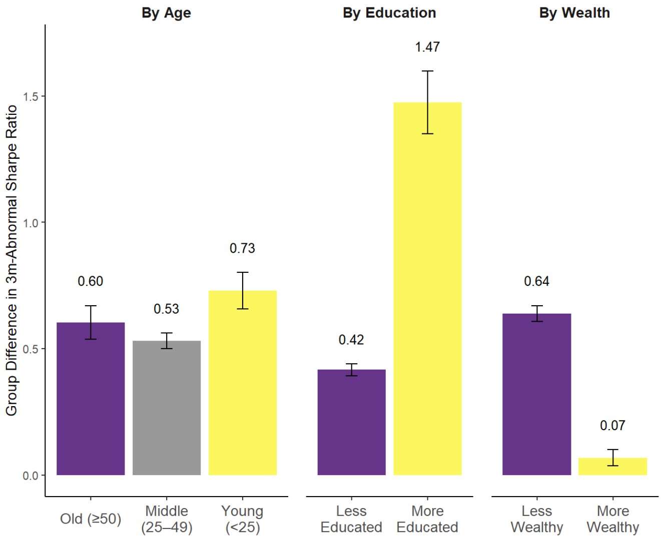

C. Portfolio Diversification



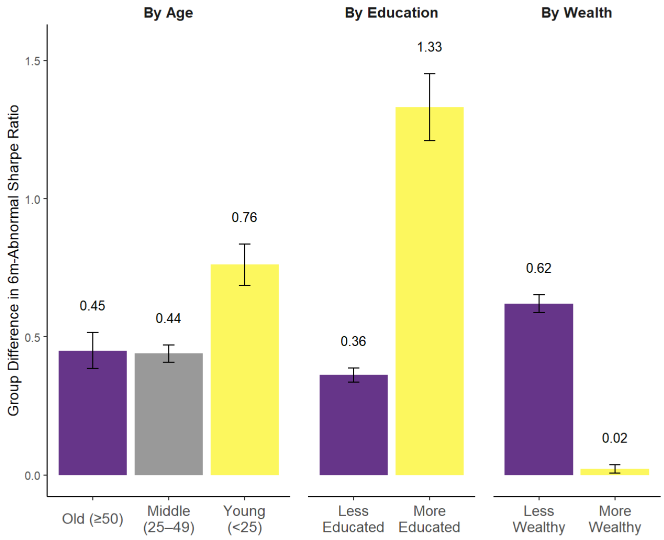

D. 1-Month Abnormal SP

**Figure A2: Heterogeneous Economic Impact Across Users' Characteristics: Treated Respondents**

This figure displays the difference in means between non-recipients in the control group (62,293 users) and responding recipients in the treated group (1,299 users) for four investment outcomes: (1) stock market participation, (2) mutual fund balance, (3) portfolio diversification (measured by platform allocation score), and (4) risk-adjusted return (measured by abnormal Sharpe ratio) over 1-, 3-, and 6-month horizons, in Panel A-F. Subgroup comparisons are presented across age (18–24, 25–49, $\geq$50), education (without vs. with a college degree), and wealth (investable assets below vs. above 50,000 RMB). Error bars represent 95% confidence intervals from two-sided t-tests.




E. 3-Month Abnormal SP




F. 6-Month Abnormal SP

**Figure A2: Heterogeneous Economic Impact Across Users' Characteristics: Treated Respondents (Continued)**

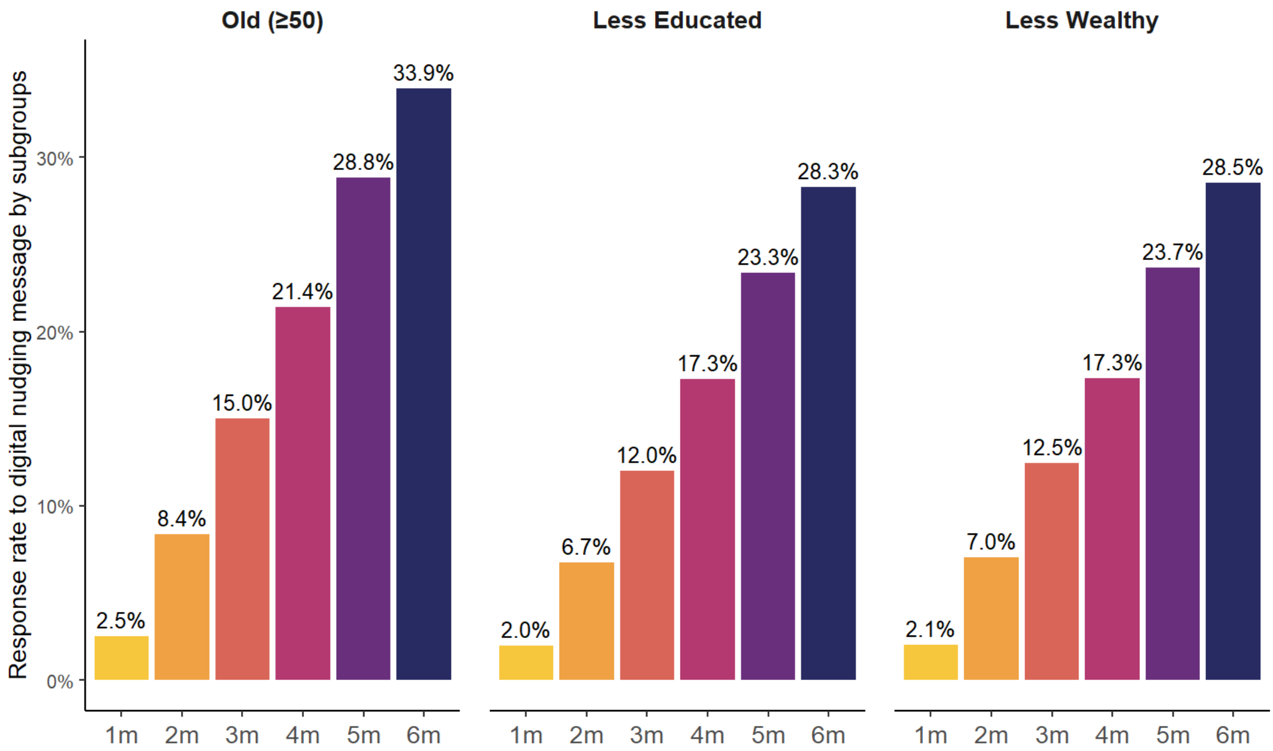



**Figure A3: Response Rates of Older, Less educated, and Less Wealthy Across Repeated Nudging Horizons**

The figure shows the proportion of users across three subpopulations–older, less educated, and less wealthy (who have a lower response rate in the first nudging month)–who responded to consecutive digital nudging messages. The vertical axis represents the rate of recorded responses, while the horizontal axis indicates the number of monthly nudges received.

**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:

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

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 *Equity Holding Ratio*, which measures the equity share held by user $i$ during the treatment. Column (1) and (2) show the impact of platform exposure on *D(Stock Market Participation)* and *Equity Holding Ratio* for treated and matched control users. $\mathbb{1}\{PlatformExposure\}_i$ is instrumented using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the service nudging 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) | Equity Holding Ratio (%) |
|---|---|---|
| | (1) | (2) |
| $\mathbb{1}\{\widehat{PlatformExposure}\}_i$ | 0.066*** | 1.924*** |
| | (8.79) | (5.87) |
| Obs | 124,586 | 124,586 |

**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:

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

where $Y_i$ represents one of six outcomes, each measuring the monthly average value during the treatment month: *Fund Balance*, *Fund Number*, *Fund Type*, *Allocation Score*, *Automatic Investment Score*, and *Fund Holding Duration*. These variables capture the average value of mutual fund balance, number of funds, distinct fund types, portfolio allocation capability, degree of automatic investment, and fund holding duration during the treatment month, respectively. We instrument $\mathbb{1}\{PlatformExposure\}_i$ using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the nudging messages 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. | Fund Balance | Fund Number | Fund Type | Automatic Investment | Allocation Score | Fund Holding Duration |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{1}\{PlatformExposure\}_i$ | 608.091*** | 0.299*** | 0.075*** | 0.344*** | 49.307*** | 1.109 |
| | (3.07) | (11.84) | (5.50) | (4.23) | (27.38) | (1.44) |
| Obs | 124,586 | 123,686 | 123,438 | 124,586 | 123,688 | 123,340 |

**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:

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

where $Y_i$ represents the investment performance, measured by the abnormal Sharpe ratio, as the difference between the investor's Sharpe ratio and the market portfolio's Sharpe ratio (SSE Composite Index). The investor's Sharpe ratio is calculated using daily mutual fund portfolio returns over 1-month (Column 1), 3-month (Column 2), and 6-month (Column 3) periods following the treatment. For users with no mutual fund holdings, the Sharpe ratio is set to zero. Column (1)-(3) report the effect of platform exposure on abnormal Sharpe ratios over the respective time horizons. $\mathbb{1}\{PlatformExposure\}_i$ is instrumented using $\mathbb{1}\{Nudge\}_i$, a dummy set to 1 for users randomly assigned to the nudging messages 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. | Abnormal Sharpe ratio | | |
|---|---|---|---|
| | 1-month | 3-month | 6-month |
| | (1) | (2) | (3) |
| $\mathbb{1}\{PlatformExposure\}_i$ | 1.058*** | 1.583*** | 1.405*** |
| | (6.04) | (9.80) | (8.29) |
| Obs | 123,741 | 123,354 | 122,888 |

**Table A4: Impact of Repeated Digital Nudging on Investment Outcomes: First-Time Respondents**

This table illustrates the mean differences in six key investment outcomes(a) stock market participation, (b) mutual fund balance, (c) portfolio diversification (measured by the platform's allocation score), (d) 1-month annualized abnormal Sharpe ratio, (e) 3-month annualized abnormal Sharpe ratio, and (f) 6-month annualized abnormal Sharpe ratio—between non-recipients in the control group and first-time respondents in the treated group across 1-6 consecutive nudging months. Investment outcomes are defined as the monthly average value of each measure across all repeated months. Each column for each investment outcome represents the number of 1st time respondents (n), the mean difference in the investment outcome between respondents and users in the control group (diff), and the corresponding p-value (p).

| | D(stock market participation) | | | mutual fund balance | | | Diversification | | |
|---|---|---|---|---|---|---|---|---|---|
| 1st respondents | n | diff | p | n | diff | p | n | diff | p |
| 1-month | 63,592 | 2.15 | 0.00 | 63,592 | 415.91 | 0.00 | 63,380 | 4.48 | 0.00 |
| 2-month | 59,101 | 2.37 | 0.00 | 59,101 | 409.52 | 0.00 | 49,011 | 5.76 | 0.00 |
| 3-month | 56,042 | 3.66 | 0.00 | 56,042 | 73.58 | 0.00 | 55,968 | 6.43 | 0.00 |
| 4-month | 53,554 | 2.00 | 0.00 | 53,554 | 2454.05 | 0.00 | 53,503 | 9.14 | 0.00 |
| 5-month | 51,379 | 3.89 | 0.00 | 51,379 | 57.89 | 0.00 | 51,341 | 12.53 | 0.00 |
| 6-month | 49,518 | 5.15 | 0.00 | 49,518 | 652.54 | 0.00 | 49,492 | 10.61 | 0.00 |
| | 1-month abnormal SP | | | 3-month abnormal SP | | | 6-month abnormal SP | | |
| 1st respondents | n | diff | p | n | diff | p | n | diff | p |
| 1-month | 63,413 | 0.42 | 0.00 | 63,320 | 0.60 | 0.00 | 63,160 | 0.538 | 0.00 |
| 2-month | 59,014 | 0.29 | 0.00 | 58,942 | 0.71 | 0.00 | 58,859 | 0.67 | 0.00 |
| 3-month | 55,974 | 1.11 | 0.00 | 55,920 | 0.64 | 0.00 | 55,885 | 0.26 | 0.00 |
| 4-month | 53,506 | 0.78 | 0.00 | 53,454 | 0.94 | 0.00 | 53,463 | 0.769 | 0.00 |
| 5-month | 51,336 | 0.95 | 0.00 | 51,313 | 0.82 | 0.00 | 51,329 | 0.98 | 0.00 |
| 6-month | 49,486 | 0.64 | 0.00 | 49,488 | 0.32 | 0.00 | 49,498 | 0.38 | 0.00 |

**Table A5: Economic Effectiveness of Repeated Nudging Among First-Time Respondents: Older, Less Educated, Less Wealthy**

This table reports the proportion of first-time older (age 50), less educated, and less wealthy respondents among the 62,293 treatment-group recipients, aggregated over the six-month repeated-nudging period, who initiated investments, along with their investment amounts and cumulative abnormal gains. Col (1), " recipients (no prior response)," shows the aggregate number of treated users who received repeated nudging across the first to sixth months (1m–6m) but had not responded before the month of their first response in each subgroup. Col (2), "1st-time respondents (%)," lists the proportion of first-time respondents among the recipients in Col (1). Col (3), " Invested respondents," shows the proportion of first-time respondents who subsequently invested in mutual funds. Col (4), "Average Fund Balance," displays the average monthly mutual fund balance for the month in which the first response was made. Col (5), "1-month abnormal SP", is the abnormal annualized Sharpe ratio calculated over the one month following the initial response, and as explained in Eq. 7 and 8. Cols (6) and (7), respectively, list the abnormal annualized Sharpe ratios over the three- and six-month horizons, corresponding to the month of the first response. Col (4)-(7) are based on the first-time respondents who have initiated mutual fund investments.

| | #1st-time respondents (1) | # Invested respondents(%) (2) | Average Fund Balance (3) | 1-month abnormal SP (4) | 3-month abnormal SP (5) | 6-month abnormal SP (6) |
|---|---|---|---|---|---|---|
| All | 2,316 | 24.22% | 2,466 | 5.19 | 4.03 | 3.43 |
| Old (>=50) | 434 | 23.04% | 5,755 | 6.14 | 4.50 | 3.54 |
| Less Educated | 1,929 | 23.54% | 1,794 | 4.56 | 3.84 | 3.09 |
| Less Wealthy | 1,872 | 22.49% | 2,335 | 5.58 | 4.63 | 3.74 |

**Table A6: Robustness I (Difference Model): First Stage - Acquisition of Platform Exposure**

This table shows coefficient estimates and associated t-statistics (in parentheses) of the Tobit and Poisson Pseudo-Maximum Likelihood model based on the matching sample:

$$Tobit : PlatformExposure_i = \alpha + \theta \mathbb{1}\{Nudge\}_i + \varepsilon_i$$

$$PPML : \mathbb{E}[PlatformExposure_i | \mathbb{1}\{Nudge\}_i] = exp(\alpha + \beta \mathbb{1}\{Nudge\}_i)$$

where Platform Exposure$_i$ is the level of the platform exposure gained by the user i. $\mathbb{1}\{Nudge\}_i$ is set to 1 for the users randomly assigned to receive the service nudging during the January campaign. Column (1) and (2) display the impact of the nudging messages on Platform Exposure$_i$ following the Tobit and PPML model, respectively. 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.

| | *Platform Exposure$_i$* | |
|---|---|---|
| | Tobit | PPML |
| $\mathbb{1}\{Nudge\}_i$ | 12.850*** | 2.826*** |
| | (21.42) | (5.98) |
| Adj $R^2$ | 0.070 | 0.001 |
| Obs | 124,586 | 124,586 |

**Table A7: Robustness I (Difference Model): 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 *Equity Holding Ratio*, which measures the equity share held by user $i$ during the treatment. Column (1) and (2) show the impact of platform exposure on *D(Stock Market Participation)* and *Equity Holding Ratio* for treated and matched control users. *Platform Exposure*$_i$ is instrumented using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the service nudging during the treatment. $\widehat{PlatformExposure}_i$ is estimated using the Tobit model (Panel A) and the PPML model (Panel B). 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.

| **Panel A. Tobit Model** | | |
|---|---|---|
| Dependent Var. | D(Stock Market Participation) | Equity Holding Ratio (%) |
| | (1) | (2) |
| *Platform Exposure*$_i$ | 0.0001*** | 0.003*** |
| | (8.90) | (5.90) |
| Obs | 124,586 | 124,586 |

| **Panel B. PPML Model** | | |
|---|---|---|
| Dependent Var. | D(Stock Market Participation) | Equity Holding Ratio (%) |
| | (1) | (2) |
| *Platform Exposure*$_i$ | 0.025*** | 0.74*** |
| | (8.90) | (5.90) |
| Obs | 124,586 | 124,586 |

**Table A8: Robustness I (Difference Model): 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:

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

where $Y_i$ represents one of six outcomes, each measuring the monthly average value during the treatment month: *Fund Balance*, *Fund Number*, *Fund Type*, *Allocation Score*, *Automatic Investment Score*, and *Fund Holding Duration*. These variables capture the average value of mutual fund balance, number of funds, distinct fund types, portfolio allocation capability, degree of automatic investment, and fund holding duration during the treatment month, respectively. We instrument *Platform Exposure*$_i$ using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the service nudging during the treatment. $\widehat{PlatformExposure}_i$ is estimated using the Tobit model (Panel A) and the PPML model (Panel B). 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.

**Panel A. Tobit Model**

| Dependent Var. | Fund Balance | Fund Number | Fund Type | Automatic Investment | Allocation Score | Fund Holding Duration |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Platform Exposure*$_i$ | 0.961*** | 0.0004*** | 0.0001*** | 0.001*** | 0.067*** | 0.001 |
| | (3.07) | (12.37) | (5.56) | (4.24) | (44.74) | (1.45) |
| Obs | 124,586 | 123,686 | 123,438 | 124,586 | 123,688 | 123,340 |

**Panel B. PPML Model**

| Dependent Var. | Fund Balance | Fund Number | Fund Type | Automatic Investment | Allocation Score | Fund Holding Duration |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Platform Exposure*$_i$ | 234.567*** | 0.099*** | 0.024*** | 0.133*** | 16.401*** | 0.342 |
| | (3.07) | (12.37) | (5.56) | (4.24) | (44.74) | (1.45) |
| Obs | 124,586 | 123,686 | 123,438 | 124,586 | 123,688 | 123,340 |

**Table A9: 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:

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

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. $\mathbb{1}\{Nudge\}_i$ is set to 1 for the users randomly assigned to receive the service nudging 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*$_{alternative,i}$ |
|---|---|
| $\mathbb{1}\{Nudge\}_i$ | 0.794*** |
| | (57.70) |
| $Adj.R^2$ | 0.026 |
| Obs | 124,586 |
| Kleibergen-Paap F-stat | 3242.56 |

**Table A10: 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 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 *Equity Holding Ratio*, which measures the equity share held by user $i$ during the treatment. Column (1) and (2) show the impact of platform exposure on *D(Stock Market Participation)* and *Equity Holding Ratio* for treated and matched control users. *Platform Exposure*$_{alternative,i}$ is instrumented using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the service nudging 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) | Equity Holding Ratio (%) |
|---|---|---|
| | (1) | (2) |
| $\widehat{Platform\ Exposure}_{alternative,i}$ | 0.002*** | 0.049*** |
| | (8.99) | (5.92) |
| Obs | 124,586 | 124,586 |

**Table A11: 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:

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

where $Y_i$ represents one of six outcomes, each measuring the monthly average value during the treatment month: *Fund Balance*, *Fund Number*, *Fund Type*, *Allocation Score*, *Automatic Investment Score*, and *Fund Holding Duration*. These variables capture the average value of mutual fund balance, number of funds, distinct fund types, portfolio allocation capability, degree of automatic investment, and fund holding duration during the treatment month, respectively. We instrument *Platform Exposure*$_{alternative,i}$ using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the nudging messages 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. | Fund Balance | Fund Number | Fund Type | Automatic Investment | Allocation Score | Fund Holding Duration |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Platform* | 15.548*** | 0.007*** | 0.002*** | 0.009*** | 1.225*** | 0.027 |
| *Exposure*$_{alternative,i}$ | (3.15) | (3.08) | (5.55) | (4.25) | (37.97) | (1.44) |
| Obs | 124,586 | 123,686 | 123,438 | 124,586 | 123,688 | 123,340 |