Platform Exposure and Household Investment: Evidence from a Large-Scale Quasi-Experiment *

Xiaomin Guo Yi Huang Qi Sun Bernard Yeung

April 2026

Abstract

This paper examines whether platform exposure to financial information services can alter household investment behavior despite widespread but underutilized digital access. Using randomly distributed nudges on a Chinese platform as an instrument, we find that the resulting increased exposure to financial information increases indirect stock investment, enhances diversification, and improves risk-adjusted returns, including for older, less educated, and less affluent users. Decomposing the exposure channels, we find that exposure to learning-oriented and non-sponsored content drives these improvements, whereas exposure to sponsored content contributes little. Our results suggest that digitalization provides a scalable, low-cost avenue for democratizing finance and improving decisions.

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

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

*Xiaomin Guo is affiliated with SUSTech Business School, email: guoxm@mail.sustech.edu.cn, Yi Huang is affiliated with Bank for International Settlements (BIS) and CEPR, email: Yi.Huang@bis.org, Qi Sun is affiliated with Shanghai University of Finance and Economics, email: sunqi@sufe.edu.cn, and Bernard Yeung is affiliated with ABFER, National University of Singapore Business School, and SUSTech Business School, email: byeung@nus.edu.sg. We appreciate very helpful comments and suggestions from Zefeng Chen, Zhi Da, Francesco D'Acunto, Rui Esteves, Will Gornall, Bing Han, Zhengyang Jiang, Charles M. C. Lee, Kai Li, Oliver Li, Randall Morck, Wenlan Qian, Alberto Rossi, Ugo Panizza, Martina Viarengo, Jian Wang, Michael Weber, Hao Zhou, and seminar participants at the Luohan Academy, the Graduate Institute, Geneva (IHEID), SUSTech, the Singapore scholars conference, the UBC Sauder Business School seminar, and University of Toronto Financial Economics seminar. We are grateful for the help and support provided by Long Chen, Yuanfang Li, and Yingju Ma at the Luohan Academy and Nan Li and Fan Yang at Ant Group. The data used in this study are proprietary and were accessed through the Open Data Program of the Luohan Academy. All data was sampled and anonymized, and was analyzed remotely within the Open Research Laboratory, a secure virtual environment accessible only for remote empirical analysis. The views expressed in this publication are those of the authors and do not necessarily reflect the views of the BIS or its member central banks.

A large body of literature documents that digitalization has profoundly transformed the financial services industry, including investment, saving, lending, and payment services.[1] This transformation has expanded financial inclusion by reducing transaction costs and enabling previously unbanked individuals to access financial services. Recent studies further show that digital technologies have broaden access to financial information, e.g., through social media (Cookson et al., 2024; Farrell et al., 2022), and can guide investors towards diversification and higher risk-adjusted returns (Rossi and Utkus, 2024). Accordingly, increased digital connectivity, through internet use and smartphones, should, in principle, promote greater stock market participation, as evidenced by Hvide et al. (2024) using Norwegian data.

However, households' direct investment in capital markets remains limited in many countries (Campbell, 2006; Haliassos and Bertaut, 1995; Panizza, 2015). Participation rates are particularly low in developing countries and even in advanced Asian economies, approximately 15%, 7%, and 6% in Japan, China, and India, respectively (Mishra, 2023). At the same time, digital and mobile device penetration is high across these economies, suggesting that access to technology alone is insufficient to close the participation gap.

This juxtaposition highlights a central puzzle: despite widespread access to digital technology and financial information, household engagement with equity markets remains persistently low. This gap suggests that access alone may be insufficient, with frictions rooted in psychological and information constraints. Behavioral inertia and limited financial literacy continue to impede participation, particularly among older, less educated, and less wealthy households (Lusardi and Mitchell, 2023). Moreover, digitalization may even exacerbate these frictions by introducing new behavioral distortions. Evidence from Robinhood shows that simplified interfaces can steer inexperienced users toward attention-driven trading (Barber et al., 2022), while an innocuous psychological bias (e.g., the response-order effect in risk-tolerance questionnaires) can influence investors' reported risk preferences and lead to different product recommendations

[1] See, e.g., D'Acunto et al. (2019) and Reher and Sokolinski (2024) on investment; Gargano and Rossi (2024) on saving; Berg et al. (2022) and Buchak et al. (2018) on lending; S. Agarwal et al. (2025), Z. Chen and Jiang (2025) and Dubey and Purnanandam (2023) on payment services; and He et al. (2023) and Babina et al. (2025) on open banking.

and portfolio allocations in automated robo-advisory markets (Yan et al., 2025). These findings suggest that the expansion of digital financial access may outpace users' financial capability.

Digital platforms can potentially help overcome behavioral inertia and close knowledge gaps by using mobile technology to nudge users toward accessible, diversified investments while simultaneously connecting them with financial knowledge and information 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 sparse.

Therefore, this paper asks whether and how platform exposure to financial information services leads previously uninvolved and inexperienced households to invest sensibly in the capital market. Its focus is on the economic and behavioral consequences of actual engagement with financial information, rather than the mere availability of such content, and assesses whether these effects reach households traditionally underrepresented in equity markets, e.g., older, less educated, and less affluent households.

China provides an interesting context: in 2022, only 14% of the population (≈200 million) invested directly in stocks (Jones et al., 2023; Tan et al., 2024), with lower participation among middle- and lower-income households. Equity accounts for less than 2% of household assets, the rest are largely in real estate (59%) and bank deposits or wealth management products (20%).[2] Moreover, recent evidence from India and China indicates that retail investors frequently engage in speculative trading, maintain poorly diversified portfolios, and earn negative long-term excess returns (V. Agarwal et al., 2025; Ayyagari et al., 2025; Jones et al., 2023). These findings underscore the importance of financial knowledge for informed portfolio choice, as private

[2]The remaining assets 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. The surveyed households report average total assets of CNY 3.18 million, implying that average equity holdings amount to less than CNY 63,600. 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.

banking and personal advisory services remain largely inaccessible to less wealthy households.

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. The platform capital market products comprise six types of mutual funds: equity, bond, hybrid, index, QDII, and gold. As of December 2022, only approximately 5% of the billion platform users maintained a balance of these products exceeding CNY 100 (roughly US$14) (Figure 1, Panel A). The remaining platform users exhibited minimal engagement: 14% held investments of CNY 0-100, and 81% were uninitiated, i.e., they had not invested in the mutual funds. Furthermore, these uninitiated users are disproportionately older, have fewer educational qualifications (no college degree), and have fewer overall investable assets as assessed by the platform (less than CNY 50,000)[3] (Figure 1, Panels 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.

Our empirical analysis leverages two core features of the platform. First, it offers free access to its financial information services: an AI-powered personalized robo-advisory (PRA) service and an integrated wealth community, through which users can access financial information and knowledge. We categorize these services into three information channels: (i) the "learning-oriented channel," via the PRA, provides tailored investment advice to support financial learning and decision-making; (ii) the "nonsponsored information channel" includes user-generated discussions and platform-curated 'super topic' offering objective updates on markets, products, and trends; and (iii) the "sponsored information channel" consists of influencer-produced content (e.g., columns, blogs, and short videos) that often carry promotional or commercial elements.

We measure a user's active engagement using *Platform Exposure*, defined as the time (in seconds) spent interacting with each information channel during the treatment period. This yields four measures per user: exposure to the learning-oriented, nonsponsored, and sponsored

[3]The platform estimate users' investable asset level based on their digital footprints, including spending behaviors and financial activities, and reflects their overall financial capacity rather than the actual assets held on the platform.

information channels, as well as their aggregate. Each measure is standardized using the observed range (max-min). These variables capture both the intensity of engagement and the channels through which users acquire financial information.

We leverage the platform's second feature, a campaign that employs simple prompts to draw users' attention to its information services, to overcome endogeneity in uninitiated users' engagement with these informational services. Each month, the platform runs a 'Wealth Festival' campaign that distributes simple digital prompts (e.g., pop-ups or banners) to users. As detailed in Section 2 ("The Effect of Platform Exposure"), assignment of these prompts to uninitiated users is random, providing quasi-experimental variation in exposure. The prompts simply direct attention to the platform's information services, and contain no additional advertising content.

We implement this strategy using the January 18, 2023, campaign. Our sample comprises approximately 0.55 million monthly active uninitiated users, defined as individuals aged 18 or above with a valid risk tolerance, who had logged in between December 18, 2022, and January 18, 2023, and had no prior platform or external risky investment experience[4], nor prior exposure to platform prompts or information channels since 2021. Users receiving campaign prompts from the treatment group; others form the control group. We define *Nudge* as a dummy indicator for prompt receipt and use it as an instrument for platform exposure in a two-stage least squares (2SLS) framework. To ensure comparability, we randomly draw a size-matched control subgroup, verify balance in observable characteristics, and further apply Coarsened Exact Matching (CEM), yielding 62,293 users per group. Figure 2 illustrates the campaign timeline and empirical design.

Nudge is a strong and highly relevant instrument: during the treatment period (January 18-February 17, 2023), 1,299 (2.1%) of treated users acquired platform exposure, compared with 34 (0.05%) of controls. We measure indirect stock market participation using $D(\textit{Stock Market Participation})_i$, an indicator equal to 1 if individual i invested in the platform's mutual funds with equity exposure (e.g., an equity-based mutual fund) during the treatment month. Instrumented aggregate platform exposure significantly increases participation: a one-unit increase raises

[4]The platform conducts its own assessment. Non-investing refers to users with no prior mutual fund investment experience, either on or off the platform, and no investment activity on the platform.

the likelihood by 2.5%. Given zero prior market engagement in both groups, this represents a meaningful behavioral shift. It also increases the equity share of users' portfolios during the treatment month.

Beyond participation, we examine a broader set of investment outcomes. These include investment engagement (mutual fund balance), and portfolio diversification (measured by i) the platform's allocation score which increases with acquired product variety, ii) the number of funds held, and iii) the number of fund types held.[5] All these outcomes are measured as monthly average value during the treatment month. Instrumented aggregate platform exposure has a significantly positive effect across all measures.

We assess risk-adjusted investment performance using the annualized Sharpe ratio over the 1-, 3-, 6-, and 9-month periods following the treatment. Portfolio returns are annualized from daily returns, and portfolio volatilities are computed as realized volatility from squared daily returns. Instrumented aggregate platform exposure significantly increases the Sharpe ratio at all horizons. Using the annualized abnormal Sharpe ratio, defined as an investor's realized Sharpe ratio minus the market portfolio, yields consistent results. Overall, instrumented aggregate platform exposure improves users' risk-adjusted returns, with effects that persist beyond the treatment period.

Turning to the three distinct information channels–learning-oriented, nonsponsored, and sponsored–we find that the nudge dummy strongly predicts engagement across all channels. However, using instrumented exposure, the correlations between actual and fitted values of stock market participation, portfolio diversification, and performance are statistically significant only for the learning-oriented and nonsponsored information channels. Principal component analysis further indicates that the first principal component is predominantly driven by variation in engagement with the learing-oriented and nonsponsored information channels.

To assess economic significance, we compare investment outcomes across six groups: the

[5]The detailed definitions and calculations of the investment outcomes are provided in Internet Appendix A1. Although the platform reports a variable for fund-holding duration, we exclude it because its construction is unclear, and several values appear implausibly extreme. Separately, while overtrading may be a concern for novice investors, we cannot examine trading frequency because transaction-level data are unavailable.

control group; treated non-respondents, treated respondents (engaging with at least one channel), and three subgroups that engage exclusively with each channel. Treated non-respondents and controls exhibit minimal changes during the treated period. In contrast, while some treated respondents did not invest, the group on average increased mutual fund balances by about CNY416 (US$58) relative to the control group's near-zero baseline and diversify into a broader set of fund types. Among channel-specific subgroups, investors engaging exclusively with the learning-oriented channel show the largest improvements in investment behavior, consistent with the belief-updating mechanism in Schoar and Sun (2024). By contrast, the sponsored information channel has little detectable effect.

We further examine heterogeneity in the effects of aggregate platform exposure across age, education, and investable-asset groups, dimensions strongly associated 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). Platform exposure increases for all in terms of participation, mutual fund holdings, portfolio diversification, and risk-adjusted performance, including the older, less educated, and less affluent users (assets< 50,000 CNY/ US$9,200). The exception is the wealthier users, who show no significant responses along any of these margins. This pattern suggests that the observed effects reflect genuine engagement and investment initiation rather than promotion-driven reallocation from external accounts, which would primarily affect wealthier investors who are more likely to hold such assets (Lusardi and Mitchell, 2023).

The effectiveness of digital nudges depends on users' response rates. Although the initial response rate is low, it rises to 28.9% after six months of repeated nudging, with a similar upward trend observed across all demographic groups, including older, less educated, and less affluent users, who are typically more susceptible to behavioral inertia. It is important to note, however, that repeated nudging may not be fully random, as the probability of receiving a nudge is greater for those who have received a nudge in the past period. As a result, the observed increase in response rates may be biased: targeted nudging could overstate apparent effects, while uniform repeated nudging would likely yield higher absolute response counts.

To measure the economic impact, we track first-time respondents across cycles, noting their

investment initiation, amounts, and risk-adjusted returns. In this focused group, about 24% have initiated investment. These new investors invest on average CNY 2,052 (≈ US$288), 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 exposure to financial knowledge and broaden inclusions.

Overall, this paper makes three contributions. First, we show that exposure to digital financial information, activated through nudges, helps investors overcome psychological and informational frictions, boosting their stock market participation and improving investment performance. Our results complement prior work showing that internet access, social media and robo-advising influence participation, beliefs, and portfolio outcomes (S. Chen et al., 2025; Cookson et al., 2024; D'Acunto et al., 2019; Farrell et al., 2022; Hvide et al., 2024; Reher and Sokolinski, 2024; Rossi and Utkus, 2024), highlighting how prompts embedded in everyday mobile use can reduce behavioral inertia and narrow financial knowledge gaps (Madrian and Shea, 2001; Thaler, 2015; Thaler and Sunstein, 2008).

Second, we document distinct effects across information channels. The most substantial benefits stem from the learning-oriented channel that provide investment guidance to informed decision-making, followed by the nonsponsored information channel that facilitate user discussions and provide objective updates on market conditions. In contrast, the sponsored information channel has little measurable impact.[6] These results highlight the importance of information design and motivate further research on the mechanisms through which different content sources shape retail investors' learning and decision-making.

Third, we show that aggregate platform exposure benefits older, less educated, and less affluent individuals, groups that often refrain from stock investing due to behavioral inertia, limited financial literacy, and heightened risk aversion (Lusardi and Mitchell, 2023). Our results suggest that prompting users to acquire financial information and knowledge through digital

[6] In contrast, deHaan et al. (2025) show negative results from exposure to sponsored channels.

information channels can meaningfully expand financial inclusion and offer practical insights for policymakers, financial educators, and investors.

The remainder of the paper is structured as follows. Section 1 describes the institutional background, data, and identification strategy. Section 2 presents the causal effects of platform exposure on participation, investment behavior, and performance, along with its key drivers, economic significance, and heterogeneity. Section 3 reports robustness checks, and Section 4 concludes.

1 Background, Platform Exposure, Variables, Treatment and Control Group

1.1 Background and our platform setting

China provides an ideal laboratory for studying the effects of platform exposure to financial information services on individual investment behaviors. First, China's online investment platforms have experienced substantial growth following 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 mutual fund indirect sales.[8]

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

[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.

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 information services, both to acquire financial information and to encourage, or even guide market participation. Our empirical goal is to identify the causal impact of such nudged exposure to these information services 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. The platform's monthly 'Wealth Festival,' initiated on the 18th of each month, directs users' attention to these services through pop-ups and homepage banners. For users who have not invested via the platform and have no prior exposure to its information services, the distribution of these prompts is random. These prompts are not advertising materials; they do not mention the platform's financial products or their performance. Instead, they direct users to click on the platform's information channels. Or they direct users to an interactive 'game page,' where completing tasks, such as visiting the personalized robo-advisor interface or accessing updated financial information, earns points with trivial value (e.g., small, inexpensive household items or supermarket coupons).

This design creates a quasi-experimental framework to address the challenge of identifying how platform exposure relates to investment behavior and outcomes (details are provided in Section 2.1). We analyze the January 2023 campaign (Jan 18 – Feb 17, 2023), the "treatment month," beyond which data are unavailable.

1.2 Platform Exposure

The key explanatory variable we want to link with changes in investment behavior and performance is platform exposure, which measures users' engagement with the platform's digitalized

financial information services. We quantify platform exposure by the time users spend interacting with each of three distinct information channels: the learning-oriented, nonsponsored, and sponsored information channels, as well as their aggregate. These three distinct information channels are defined as follows:

a. Learning-oriented channel: This channel captures users' acquisition of financial knowledge and informed decision-making through the Personalized Robo-Advisor (PRA), an AI-driven assistant that provides information on financial markets and products and offers investment guidance to enhance financial literacy, without executing trades on users' behalf. The PRA is tailored to individual investor needs and provides unrestricted access, irrespective of time, location, wealth, or income, and unlike traditional advisory services, does not require a subscription. It enables users to explore a wide range of financial products, gain insights into market trends, and access comprehensive financial education content alongside personalized investment guidance. Moreover, the PRA assists users in monitoring their portfolios and provides alerts when they may be making imprudent investment decisions, such as selling or acquiring risky assets during market downturns.

b. Nonsponsored information channel: This channel captures investors' engagement with financial information shared and discussed within the platform's wealth community, including user-generated posts in the Forum[9] and platform-curated 'super topic' sections[10] that provide objective updates on market developments, financial news, and emerging trends. The content accessible through this channel is non-commercial and not sponsored.

c. Sponsored information channel: This channel captures investors' engagement with financial content created primarily by influencers, including columns, blogs, and short videos. The content is diverse, ranging from attention-grabbing posts, and investment recommendations to financial products and personal reading of types of financial products and market conditions. Very often, there are explicit or implicit commercial elements. By engaging with this channel, users are

[9]The forum, built inside the wealth community, covers a wide range of financial topics, including specific products and indexes. Users can ask questions, share ideas, and discuss experiences in real time, fostering peer-to-peer learning and enhancing the community's collective financial knowledge. See, Brown et al., 2008; Guiso and Jappelli, 2005; Hayta, 2008

[10]The super-topic section highlights trending financial topics, providing real-time news and analysis to enhance users' understanding of market dynamics and support more informed investment decisions.

likely to encounter a mix of informative and promotional material that may influence their decision-making.

We normalize each user-level measure of platform exposure to a [0,100] scale using min-max scaling according to the following equation:

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

where i represents the sample individual; Total Time$_i$ denotes the total amount of time user i spends with digitalized financial information services provided through three information channels; max(Total Time$_i$) and min(Total Time$_i$) represent the maximum and minimum values of the total time spent across all users in the sample, respectively. If an individual did not use any digitalized financial information services, we mark her $Platform\ Exposure_i$ as zero. $Platform\ Exposure_i$ is a monthly measure for aggregate platform exposure, and we omit the month-year subscript. The same notation can be extended with an additional subscript to index the three information channels described above, yielding Platform Exposurei, a, Platform Exposurei, b, and Platform Exposurei, c.

The preceding equation and computation assess the intensive margin of platform exposure, capturing the depth of users' engagement. In addition to this measure, we also assess the extensive margin using a binary variable that indicates whether a user engages with any financial information channel 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 information services.

1.3 Other Variables

Our empirical work also needs data on (i) users' characteristics, (ii) users' response to the prompts in the treatment month and thus their usage (or non-usage) of the platform's digital financial information 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 (a platform-based risk tolerance measure derived from the investor's responses to the platform's periodic risk assessment survey). The risk level ranges from 0 to 5.

The second dataset is a dummy variable indicating whether a user received digital prompts promoting the engagement with platform's financial information services, which could lead them to acquire the four types of platform exposure (aggregate and three channel-specific engagements). Our IV $Nudge_i$ equals 1 if user i received digital prompts during the treatment period, from January 18 to February 17, 2023; 0 otherwise.

The third dataset contains monthly observations on users' investment behaviors and performance. We examine seven investment outcome variables. The first is *Stock Market Participation*, defined as an indicator equal to 1 if a user invested in mutual funds with equity exposure during the treatment month, and 0 otherwise. The remaining five outcomes: *Equity Holding Ratio, Fund Balance, Fund Number, Fund Type*, and *Allocation Score*, capture users' portfolio equity holding share, investment in mutual funds, and the breadth and composition of their portfolios.

Fund Number and *Fund Type* serves as proxies for diversification. *Allocation Score*, computed by the platform's investment team (Internet Appendix A1), provides an additional measure of portfolio diversification and asset allocation quality.

For each investor, portfolio returns are annualized using daily returns, and portfolio volatilities are computed as realized volatilities using squared daily returns.

1.4 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 had logged into the platform Dec 18 2022-Jan 17 2023, one month before the January 2023 campaign) above 17 of age and who had no prior platform exposure, no history of investment

activity, and had not received any service prompts before the start of the treatment month (Jan 18 2023). More precisely, the population comprises users with zero *Platform Exposure*$_i$ and *Nudge*$_i$ from January 1, 2021 to Jan 17, 2023.

During the treatment month, some individuals in the extracted population received randomly distributed prompts that draw their attention to the platform's information 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 verify that the two groups exhibit statistically indistinguishable distributions across all observed user 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 level, 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 before and after the treatment (October 18, 2022 - July 17, 2023) for both the treated and control groups.[11]

1.5 Summary Statistics

Table 1 shows that the distributions of demographic characteristics and previous financial status for the treated (Panel A) and non-treated users (Panel B) before matching are 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,

[11] 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)

based on Coarsened Exact Matching (CEM), have similar demographic characteristics and risk levels before the treatment, as shown in Table 2. The mean difference for each variable is no more than 0.1. We also test the null 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, with 56% male. Only 13% hold a bachelor's degree or higher, which aligns with China's overall education attainment. 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 (≈ US$ 6,824) or more.

2 The Effects of Platform Exposure

This section examines the impact of platform exposure on stock market participation, investment behavior, and performance. We outline our identification strategy and present baseline causal estimates from a two-stage least squares framework, using randomized prompts as an instrument for platform exposure to financial information services. We then assess the economic significance of the nudging-induced engagement with the information channels. We compare outcomes across six groups: the control group; treated non-respondents; treated respondents who engage with at least one channel; and three subgroups that engage exclusively with each channel. Finally, we explore heterogeneity in the effects across demographic groups.

2.1 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 1.2, 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 information services to acquire financial knowledge and information. 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 financial information services and shifts in investment behaviors.

We address identification challenges by leveraging the platform's marketing campaign, which delivers randomized prompts via pop-up messages and banners during the campaigning period (Jan 18-Feb 17, 2023). Users receive these prompts during the treatment month have $Nudge_i$=1, as defined in Section 1.3, and are in the treated group, whereas members of the CEM matched control group 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 Equation 2 is the intensive margins measure of aggregate platform exposure the user i acquires during the treatment on a scale ranging from 0 to 100, as defined in Equation 1; $\mathbb{1}\{PlatformExposure\}_i$ in Equation 3 is the extensive margins measure, a dummy variable equal to 1 if the user i has used digital financial information 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 changes in outcome Y – users' stock market participation, investment behaviors and performance – using the predicted $PlatformExposure_i$ and $\mathbb{1}\{PlatformExposure\}_i$ respectively as the main predictors:

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

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

The parameter of interest is β, which measures the mean difference in investment outcomes after acquiring platform exposure; that is, after gaining exposure to the digital financial information services.

While one might attempt to estimate channel-specific effects by running separate 2SLS regressions for each channel engagement following Equations 2 and 4, such estimates are not valid because the three channels are highly correlated, making the exclusion of the other channels untenable (results available upon request). Alternatively, jointly instrumenting all three channels with the same nudging instrument and including the three fitted values in the second stage is infeasible due to near-perfect multicollinearity. These issues imply that standard 2SLS cannot isolate the contribution of each channel within the baseline specification. To identify the main drivers of the baseline effects, we employ a set of complementary measures designed to disentangle the explanatory power of each channel; the detailed results are presented in Subsection 2.3.

2.2 Causal Effects of Aggregate Platform Exposure

2.2.1 First Stage: instrumentalizing aggregate platform exposure

In the first stage, we measure aggregate platform exposure in intensive margins to estimate how digital prompts affect the total time engaging with all three information channels.

Table 3 shows our first-stage regression results based on Equations 2 and 3. Columns (1) and (2) report the results regarding aggregate platform exposure in intensive and extensive margins. Column (1) shows that digital prompts can increase the intensity of aggregate platform exposure on average by 0.05. In column (2), we find that the instrument IV coefficient θ identifies a 2.0% increase in the probability of an uninitiated user acquiring aggregate platform exposure during the treatment period. The parameter θ is close to the mean difference in aggregate 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 aggregate platform exposure between two groups as our instrumentalised estimator ($Platform\ Exposure_i$) for the second

stage regression. We also find that the Kleibergen-Paap F-statistic for these first-stage regressions is very large, indicating that the dummy indicator *Nudge* is a strong instrument.

2.2.2 Second Stage: Aggregate Platform Exposure and Stock Market Participation

We first analyze how aggregate platform exposure affects users' participation in the stock market.

The dependent variables are *D(Stock Market Participation)* and $EquityRatio$. *D(Stock Market Participation)* is an indicator equal to 1 if individual i invested in mutual funds with equity exposure (e.g., an equity-based mutual fund) 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 aggregate Platform Exposure (intensive) as our baseline regressor in the second-stage regression and report the results for aggregate Platform Exposure (extensive) in the Internet Appendix.

Column (1) in Table 4 displays the impact of aggregate platform exposure on *D(Stock Market Participation)* during the treatment month. We find that a one-unit increase in aggregate 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 platform exposure may facilitate broader retail participation by mitigating behavioral inertia among previously inactive investors, with effects operating through prompted engagement that increases exposure to financial knowledge and information.

Column (2) shows that a unit increase in aggregate 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 is not only statistical significance but also economically non-trivial. Table A1 in the Internet appendix shows that measuring aggregate platform exposure using the extensive margin yields a similar significant result, indicating that acquiring aggregate 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 prompt novice investors' participation in the equity market through enticing them to engage in information services that disseminate financial information and knowledge.

2.2.3 Second Stage: Aggregate Platform Exposure and Investment Behaviors

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

Similar to the impact on stock market participation, we find that during the treatment month, there is a significant and economically non-trivial increase in all users' investment behavior, 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 of fund types also show significant growth, highlighting the increase in portfolio diversification. Additionally, platform exposure can improve portfolio allocation by 21.319. Compared to the pre-treatment value of zero, the observed gains is economically significant, representing 21.32% of the full 0–100 scale. These improvements indicate substantial progress in participants' investment engagement and sophistication.

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 (Internet Appendix). These results reveal that platform exposure can significantly enhance users' portfolio diversification and allocation skills.

2.2.4 Second Stage: Aggregate Platform Exposure and Performance

We analyze the short-term effects of aggregate platform exposure on portfolio returns over 1, 3, 6 and 9 months. To assess performance, we adopt the annualized Sharpe ratio as our performance metric. 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 Equation A1 (Internet Appendix). Users with no mutual fund holdings during the analysis window are assigned a Sharpe ratio of zero.

Table 6 reports results for all sample users. Columns (1)–(4) show that the treated group exhibits significantly higher Sharpe ratios than the control group over 1-, 3-, 6-, and 9-month horizons. During the treatment month, each unit increase in aggregate platform exposure is associated with a 0.456-unit gain in the Sharpe ratio. This effect persists: treated users outperform controls by 0.626, 0.551, and 0.376 units at the 3-, 6-, and 9-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 may be affected by noise. We do not restrict control group users from receiving digital nudges after the treatment period (Jan 18–Feb 17, 2023), so some control users may be exposed to digital nudges in subsequent months, potentially attenuating the estimated treatment effects on longer-term performance (i.e., the 3-, 6-, and 9-month Sharpe ratios). The results remain consistent when we restrict the control group to users who are not exposed to digital nudges during the corresponding 3-, 6-, and 9-month horizons.[12]

2.3 Channel-Level Drivers of the Baseline Effects

To identify the drivers of baseline effects, we examine platform exposure to three distinct information channels and assess their contributions. This approach allows us to distinguish whether the observed improvements in capital market participation, portfolio diversification, and performance are driven by exposure to the learning-oriented, non-sponsored, or sponsored information channels. We further employ several measures to assess the explanatory power and economic impact of each channel.

[12]The results are available upon request. After restricting post-treatment nudges, the control group sample sizes are 55,783, 49,462, and 37,205 for the 3-, 6-, and 9-month horizons, respectively.

First, we decompose aggregate platform exposure into three subcomponents: $Platform\text{-}Exposure_{i,a}$, $PlatformExposure_{i,b}$, and $PlatformExposure_{i,c}$, each corresponding to information channels a, b, and c as in Subsection 1.2 and measured by the total interaction time with that channel. To ensure comparability across channels, we standardize each component to a 0–100 scale. We could then re-estimate the baseline 2SLS specification separately for each channel, using the channel-specific predicted exposure instrumented by the nudging indicator as the key regressor in the second stage (Equation 4). However, the resulting coefficients would lack meaningful economic interpretation because of omitted-variable bias. Including all predicted channel-specific exposure measures simultaneously in the second stage is also infeasible due to perfect collinearity. Therefore, we adopt an alternative approach to assess the explanatory power of each channel. Specifically, we examine the correlation between the realized outcome y and the predicted outcome $\hat{y}$ generated from the channel-specific exposure measure. A stronger corr(y,$\hat{y}$) indicates that variation in the outcome is better accounted for by exposure through that channel. As reported in Table 7, the sponsored information channel shows weak, statistically insignificant correlations, suggesting limited predictive content despite its significance in the 2SLS regressions. By contrast, the learning-oriented channel shows the highest correlation with realized outcomes, indicating that it is the primary channel through which platform exposure translates into meaningful economic improvements.

Second, we employ Principal Component Analysis (PCA) to assess the relative contribution of each information channel to the common component underlying overall platform exposure. The first principal component is used as an aggregate measure of exposure since it captures the largest share of variance across the three channels. Table 8 shows that the first principal component is mainly driven by the learning-oriented channel (factor loading = 0.7066) and the nonsponsored information channel (0.7070). In contrast, the sponsored information channel shows a negligible loading (0.0285) and contributes almost no variance to the common component. Consistent with this pattern, relatively few treated users engaged with the sponsored information channel, and those who did spend substantially less time interacting with it. Together, these findings indicate that the sponsored information channel plays a limited role in shaping the underlying structure of platform exposure, aligning with its weak predictive content

for investment behavior.

However, these two approaches still implicitly assume that each channel operates independently. In practice, interactions across channels are highly correlated (e.g., users often engage with multiple channels simultaneously), so the estimated effects may capture spillovers rather than the isolated impact of a single channel. To address this concern, we focus on the impact on treated users who received nudges and engaged exclusively with one of information channels. This approach helps mitigate cross-channel contamination and better enables us to identify the unique contribution of each channel. Nevertheless, this design may introduce self-selection bias, as the decision to interact with a particular channel is itself an endogenous choice driven by user preferences or characteristics. Therefore, while this strategy improves isolation of channel-specific effects, the results should be interpreted with caution, acknowledging potential selection into channels. We present the detailed empirical findings based on this exclusive-engagement sample in Section 2.4.2 below.

2.4 Treated Respondents

Building on the causal analysis of aggregate platform exposure and its channel-specific effects, we next assess the economic significance by examining how realized user engagement affects stock market participation, investment behavior, and performance. The focus is on those who received and responded to digital nudges and subsequently acquired platform exposure, whom we refer to as treated respondents.

2.4.1 Investment Outcomes Across User Engagement Groups

Figure 4 illustrates the impact of platform exposure to financial information services on investment outcomes (capital market participation, diversification, and performance) across six groups: the control group (non-recipients), treated non-respondents, treated respondents who engage with at least one channel; and three subgroups that engage exclusively with each channel. We begin by focusing on the first three groups. The results indicate that significant changes occur only among the treated respondents. In contrast, individuals who received the prompts

but either ignored them or clicked without engaging with any financial information services exhibited behaviors similarly to the control group. However, the difference between the responding and non-responding treated users could be due to self-selection. To mitigate this concern, we restrict the comparison to treated respondents and individuals who did not receive digital prompts. Under this specification, the difference can be interpreted as the effect of exposure to information channels induced by nudging.

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 aggregate platform exposure, equivalent to 77 seconds (as opposed to almost 0 exposure among those in the control group). They are 21.1% more likely to initiate mutual fund investments and have a 2.2% higher probability of participating in the stock market than their control counterparts (who 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 (allocation score, fund number and type) and higher risk-adjusted returns during the treatment month. Moreover, their improved investment performance persists over longer horizons (3, 6, and 9 months). The treated non-respondents behaved similarly to the control group, highlighting that only those who overcome behavioral inertia to gain platform exposure experience improvements in investment outcomes.

2.4.2 Channel-Specific Effect

Beyond the baseline effects of aggregate platform exposure, we examine channel-specific impacts by comparing the three treated respondent subgroups. Consistent with our earlier evidence on the strong predictive power of the learning-oriented channel, users who engaged exclusively with this channel show the largest improvements across most investment outcomes, often exceeding the baseline effects for the full treated sample. By contrast, exposure to the sponsored information channel has a negligible impact on stock market entry, changes in mutual fund balances, portfolio diversification, and the Sharpe ratio. Overall, these patterns indicate that learning-oriented engagement is the primary driver of behavioral change, followed by exposure

to the nonsponsored information channel. They underscore the importance of informational neutrality and depth, as well as skill acquisition in shaping investment decisions.

2.4.3 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 a cumulative effect, as shown in Figure 5: the response rate increases steadily with each successive monthly nudging, reaching 28.9% after six iterations. Among users receiving two to six consecutive nudges, response rates increase from 7.2% (1,186 of 16,527) to 12.7% (1,193 of 9,365), 17.9% (1,089 of 6,095), 24.1%(991 of 4,115), and finally 28.9% (928 of 3,214).

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, compared with 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 (Internet Appendix).

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

2.4.4 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 who initiated investments, the amounts invested, and their cumulative gains.

Table 9 Panel A reports results for all first-time respondents with any platform exposure. Column 1 reports users who receive repeated nudges from months 1 to 6, conditional on no prior responses before their first month of engagement. Column 2 displays the percentage of

these users who respond and gain exposure for the first time, showing a slight upward trend. Column 3 presents the percentage of first-time respondents who initiate 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 annualized Sharpe ratios over the 1-,3-, and 6-month horizons.

Panel B restricts the sample to users with at least one minute of aggregate platform exposure. The results show that greater aggregate platform exposure is associated with a higher likelihood of initiating mutual fund investments, larger portfolio allocations, and improved risk-adjusted performance. The only exception arises in Month 4, when both fund performance and the marketwide Sharpe ratio were substantially negative due to a broad market downturn, thereby attenuating the estimated performance effect for that period.

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, on average, significantly greater mutual fund investments on average over the 6-month horizon than 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 nudges administered by the platform may not be fully random, as the likelihood of receiving a nudge in the subsequent month (t+1) is positively correlated with receiving a nudge in the treatment month (t). We therefore caution that while the observed rising patterns provide useful information, they are not precise: targeted nudging may inflate the apparent response rate and effects, whereas uniform, repeated nudging may yield more responses in sheer numbers. Given the minimal cost of digital nudging, we recommend that platforms consider expanding repeated nudging strategies to maximize user engagement and promote broader retail participation in financial markets, particularly given the persistent behavioral inertia exhibited by many users.

2.5 Heterogeneous Effects of Aggregate Platform Exposure on Sub-Groups

While the preceding results document the causal effect of aggregate platform exposure on stock market participation and investment outcomes, the magnitude of these effects may vary across user characteristics. These patterns provide additional evidence on the mechanism through which platform exposure affects investment behavior. Figure 1 shows that a significant proportion of platform users who have not yet invested in mutual funds are older, less educated, and less wealthy. These individuals are more likely to have fewer investable resources and face informational barriers to financial market participation, including lower financial literacy and limited access to professional financial advice (Lusardi and Mitchell, 2014; 2023). Yet, these groups' marginal gains in stock investing could be high. Therefore, one would hope that platform exposure could indeed increase the stock market participation and investment performance of the older individuals, those with less education, and those with fewer investable assets.

To examine heterogeneous effects, we estimate the baseline IV regressions from Tables 3-5 across key demographic groups defined by age (18–24, 25–49, and 50+), education (without or with a college degree), and investable assets (below or above CNY 50,000). The outcome variables capture three dimensions of investment behavior: 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 Sharpe ratio).

Overall, the effects of aggregate platform exposure are stronger for older, less educated, and less wealthy users. These groups exhibit larger increases in equity participation, mutual fund holdings, portfolio diversification, and risk-adjusted returns. These patterns are consistent with the interpretation that the platform's information services help alleviate informational barriers faced by investors who are traditionally less engaged in capital markets.

Figure 6 reports heterogeneous responses in the acquisition of aggregate platform exposure. Younger, more educated, and less wealthy users are more likely to engage with the platform's financial information services when nudged, whereas wealthier individuals exhibit little response to the prompts. Younger users may be more comfortable navigating digital platforms, while more

educated individuals may find it easier to process financial information. Less wealthy users may also view digital financial information services as an accessible and low-cost source of financial information and knowledge.

Panels A–C of Figure 7 then present heterogeneous treatment effects on investment outcomes. Aggregate platform exposure significantly increases stock market participation and mutual fund holdings across most groups except for wealthier individuals, with particularly strong increases among older, less educated, and less wealthy users. These groups also exhibit greater improvements in portfolio diversification and risk-adjusted performance following exposure.

In contrast, we find little evidence that wealthier users adjust their investment behavior following the nudges. This pattern is consistent with the view that the platform primarily alleviates informational constraints faced by less advantaged investors. Wealthier individuals, by their wealth status, may have already had prior exposure to financial markets and access to alternative sources of financial advice, such as professional wealth managers or private banking services, reducing their reliance on the platform's information services.

Importantly, this heterogeneity also helps rule out a simple advertising interpretation of the nudges. If the prompts merely acted as product promotion, wealthier users who possess greater investable resources and are more likely to already participate in financial markets would be expected to respond by reallocating assets toward the platform's investment products. Instead, their limited response to the nudges and the absence of meaningful adjustments in investment behavior suggest that the intervention operates primarily through information acquisition rather than advertising.

2.5.1 Economic Effectiveness: Older, Less wealthy, and Less educated

To further assess the economic impact of aggregate platform exposure 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 (investable asset < CNY50,000) — and compare them with users in corresponding subgroups in the control

group. Figure A2 (Internet Appendix) shows that aggregate platform exposure 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, Internet Appendix) 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 under-represented 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 gains. Table A5 (Internet Appendix) 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 among all treated first-time respondents. Furthermore, the ranking of the effectiveness of the three information channels (learning, nonsponsored, and sponsored) also mimics that reported for the full sample.

3 Robustness Check

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

Given that the distribution of aggregate 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 aggregate platform exposure. As shown in Table A6 (Internet Appendix), digital prompts significantly increase aggregate platform exposure under both the Tobit and PPML specifications. In the second stage, aggregate platform exposure estimated from either model continues to have a significant positive effect on stock market participation and investment behaviors (Table A7-A8, Internet Appendix). 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.

4 Conclusions

Digital platform exposure, as used in this paper, refers to the prompted engagement with the platform's financial information services to acquire financial information and knowledge through three distinct information channels. 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, recognizing that easy access to risky stock investments can cause harm without proper knowledge, we examine whether nudging potential investors toward exposure to digital information services can enhance household stock market participation, improve investment decisions, and ultimately boost investment performance.

Using a quasi-experimental research design, we find that a digital platform can nudge its users towards greater exposure to digital financial information services with 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 Sharpe ratio of their investment portfolio.

Moreover, we find notable heterogeneity across the platform's information channels. The learning-oriented and nonsponsored information channels are the primary drivers of behavioral change, generating the largest increases in investment initiation, and portfolio diversification,

and exhibiting the strongest predictive power for investment outcomes. In contrast, the sponsored information channel contributes little to explaining changes in investment behavior. These findings highlight that the effectiveness of platform exposure depends on the channel's informational depth and neutrality, underscoring the importance of high-quality, user-driven financial learning to enhance household investment decisions.

This study also shows that the impact of platform exposure varies across demographic groups-age, education, and affluence. All subgroups, particularly the younger and more educated, gain platform exposure following nudges, except the more affluent. Also, the effects on investment engagement, portfolio diversification, and performance are also pronounced, including the older, less educated, and less wealthy individuals, except for the more affluent. The older, less educated, and less affluent subgroups 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 participation. Therefore, the results highlight that nudging potential investors towards engagement with financial information services 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, with consecutive nudging, newly responsive recipients each month exhibit improved investment efficiency, marked by greater diversification and persistently favorable risk–return 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 information and 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 platform exposure to financial information services 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 exploit digital platform exposure to take advantage of unsuspecting users. Additional research is needed to more fully identify and quantify the effects of platform exposure on household welfare.

References

Agarwal, S., Qian, W., Ren, Y., Tsai, H.-T., & Yeung, B. (2025). The real impact of FinTech: Evidence from mobile payment technology. *Management Science*.

Agarwal, V., Ghosh, P., Prabhala, N., & Zhao, H. (2025). Animal spirits on steroids: Evidence from retail options trading in india.

Ayyagari, M., Ghosh, P., Kulkarni, N., & Cheng, Y. (2025). Open payment infrastructure and market participation: The role of interoperability in financial inclusion. *Available at SSRN 5353153*.

Babina, T., Bahaj, S., Buchak, G., De Marco, F., Foulis, A., Gornall, W., Mazzola, F., & Yu, T. (2025). Customer data access and fintech entry: Early evidence from open banking. *Journal of Financial Economics*, *169*, 103950.

Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-induced trading and returns: Evidence from robinhood users. *The Journal of Finance*, *77*(6), 3141–3190.

Berg, T., Fuster, A., & Puri, M. (2022). FinTech lending. *Annual Review of Financial Economics*, *14*(1), 187–207.

Briggs, J., Cesarini, D., Lindqvist, E., & Östling, R. (2021). Windfall gains and stock market participation. *Journal of Financial Economics*, *139*(1), 57–83.

Brown, B. B., Bakken, J. P., Ameringer, S. W., & Mahon, S. D. (2008). A comprehensive conceptualization of the peer influence process in adolescence. *Understanding peer influence in children and adolescents*, *13*, 17–44.

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of financial economics*, *130*(3), 453–483.

Bucher-Koenen, T., Alessie, R. J., Lusardi, A., & Van Rooij, M. (2021). *Fearless woman: Financial literacy and stock market participation*. National Bureau of Economic Research.

Campbell, J. Y. (2006). Household finance. *The journal of finance*, *61*(4), 1553–1604.

Chen, S., Peng, L., & Zhou, D. (2025). Wisdom or whims? decoding the language of retail trading with social media and AI.

Chen, Z., & Jiang, Z. (2025). The liquidity premium of digital payment vehicle. *Management Science*, *71*(7), 5605–5624.

Christelis, D., Jappelli, T., & Padula, M. (2010). Cognitive abilities and portfolio choice. *European Economic Review*, *54*(1), 18–38.

Cookson, J. A., Lu, R., Mullins, W., & Niessner, M. (2024). The social signal. *Journal of Financial Economics*, *158*, 103870.

D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The promises and pitfalls of robo-advising. *The Review of Financial Studies*, *32*(5), 1983–2020.

deHaan, E., Huang, A. H., Kannan, S., & Qiu, L. (2025). Social media livestreaming: Investor information or persuasion? *Available at SSRN 5101849*.

Dubey, T. S., & Purnanandam, A. (2023). Can cashless payments spur economic growth? *Available at SSRN 4373602*.

Duflo, E., & Saez, E. (2003). The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *The Quarterly journal of economics*, *118*(3), 815–842.

Farrell, M., Green, T. C., Jame, R., & Markov, S. (2022). The democratization of investment research and the informativeness of retail investor trading. *Journal of Financial Economics*, *145*(2), 616–641.

Fowlie, M., Greenstone, M., & Wolfram, C. (2018). Do energy efficiency investments deliver? evidence from the weatherization assistance program. *The Quarterly Journal of Economics*, *133*(3), 1597–1644.

Gargano, A., & Rossi, A. G. (2024). Goal setting and saving in the FinTech era. *The Journal of Finance*, *79*(3), 1931–1976.

Guiso, L., & Jappelli, T. (2005). Awareness and stock market participation. *Review of Finance*, *9*(4), 537–567.

Haliassos, M., & Bertaut, C. C. (1995). Why do so few hold stocks? *the economic Journal*, *105*(432), 1110–1129.

Hayta, A. B. (2008). Socialization of the child as a consumer. *Family and Consumer Sciences Research Journal*, *37*(2), 167–184.

He, Z., Huang, J., & Zhou, J. (2023). Open banking: Credit market competition when borrowers own the data. *Journal of financial economics*, *147*(2), 449–474.

Hvide, H. K., Meling, T. G., Mogstad, M., & Vestad, O. L. (2024). Broadband internet and the stock market investments of individual investors. *The Journal of Finance*, *79*(3), 2163–2194.

Jones, C. M., Shi, D., Zhang, X., & Zhang, X. (2023). Retail trading and return predictability in china. *Journal of Financial and Quantitative Analysis*, 1–37.

Kaiser, T., Lusardi, A., Menkhoff, L., & Urban, C. (2022). Financial education affects financial knowledge and downstream behaviors. *Journal of Financial Economics*, *145*(2), 255–272.

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *American Economic Journal: Journal of Economic Literature*, *52*(1), 5–44.

Lusardi, A., & Mitchell, O. S. (2023). The importance of financial literacy: Opening a new field. *Journal of Economic Perspectives*, *37*(4), 137–154.

Lusardi, A., Mitchell, O. S., & Curto, V. (2010). Financial literacy among the young. *Journal of consumer affairs*, *44*(2), 358–380.

Madrian, B. C., & Shea, D. F. (2001). The power of suggestion: Inertia in 401 (k) participation and savings behavior. *The Quarterly journal of economics*, *116*(4), 1149–1187.

Mishra, A. (2023). *How many people are investing in the markets?* https://www.swastika.co.in/blog/population-participating-in-stock-markets-by-country

Panizza, U. (2015). Billions on the sidewalk improving savings by reducing investment mistakes. *Available at SSRN 2828695*.

Reher, M., & Sokolinski, S. (2024). Robo advisors and access to wealth management. *Journal of Financial Economics*, *155*, 103829.

Rossi, A. G., & Utkus, S. (2024). The diversification and welfare effects of robo-advising. *Journal of Financial Economics*, *157*, 103869.

Schoar, A., & Sun, Y. (2024). *Financial advice and investor beliefs: Experimental evidence on active vs. passive strategies*. National Bureau of Economic Research, Inc.

Tan, L., Zhang, X., & Zhang, X. (2024). Retail and institutional investor trading behaviors: Evidence from china. *Annual Review of Financial Economics*, *16*(1), 459–483.

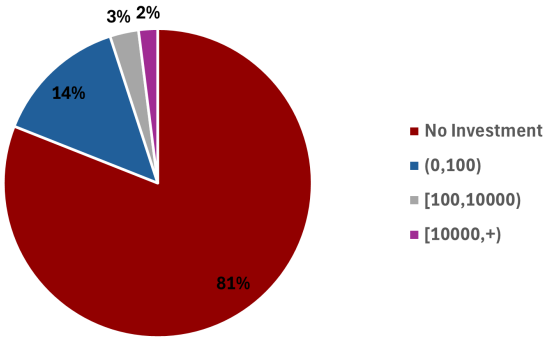
Thaler, R. H. (2015). *Misbehaving–the making of behavioral economics*. WW Norton & Company.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.

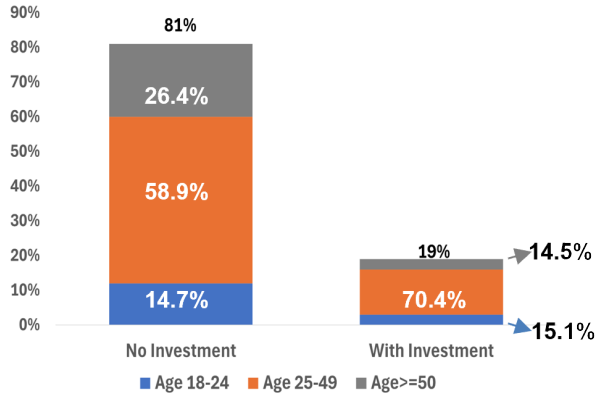
Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial economics*, *101*(2), 449–472.

West, S. G., Duan, N., Pequegnat, W., Gaist, P., Des Jarlais, D. C., Holtgrave, D., Szapocznik, J., Fishbein, M., Rapkin, B., & Clatts, M. (2008). Alternatives to the randomized controlled trial. *American journal of public health*, *98*(8), 1359–1366.

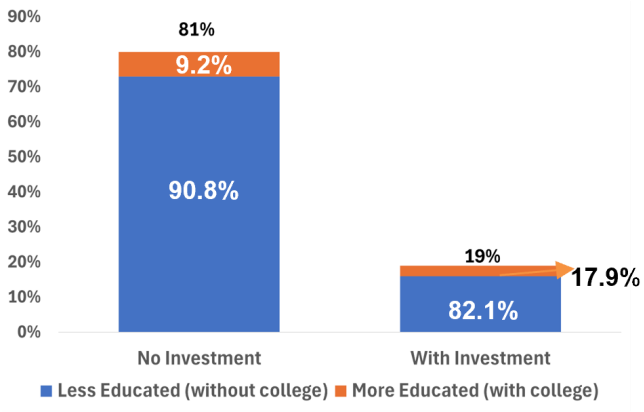
Yan, H., Wang, Z., Yuan, Y., Qiu, X., Xiang, J., Xiao, Y., & Davidson, E. (2025). FinTech brings a bias from psychology labs to a two-trillion-dollar market. *Available at SSRN 5429895*.



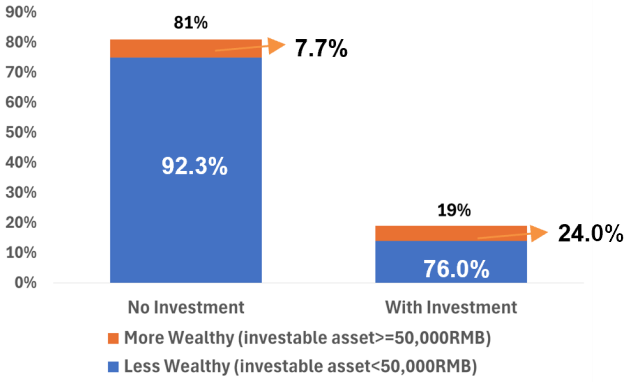
Panel A. The Overall Distribution



Panel B. By Age



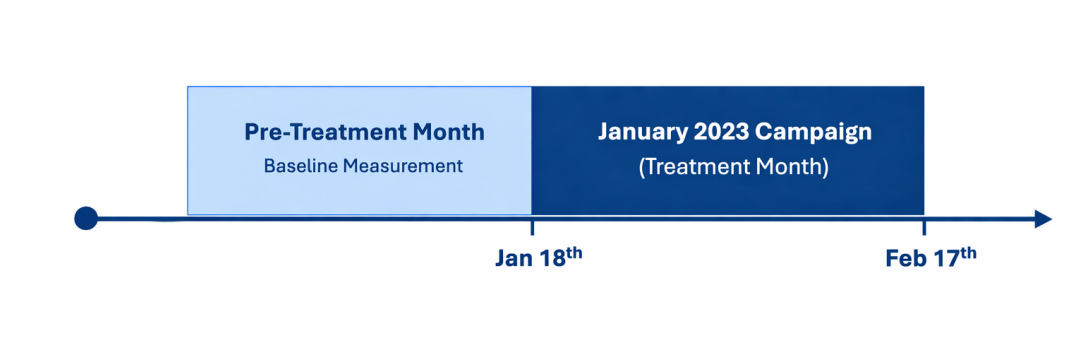
Panel C. By Education Level



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).



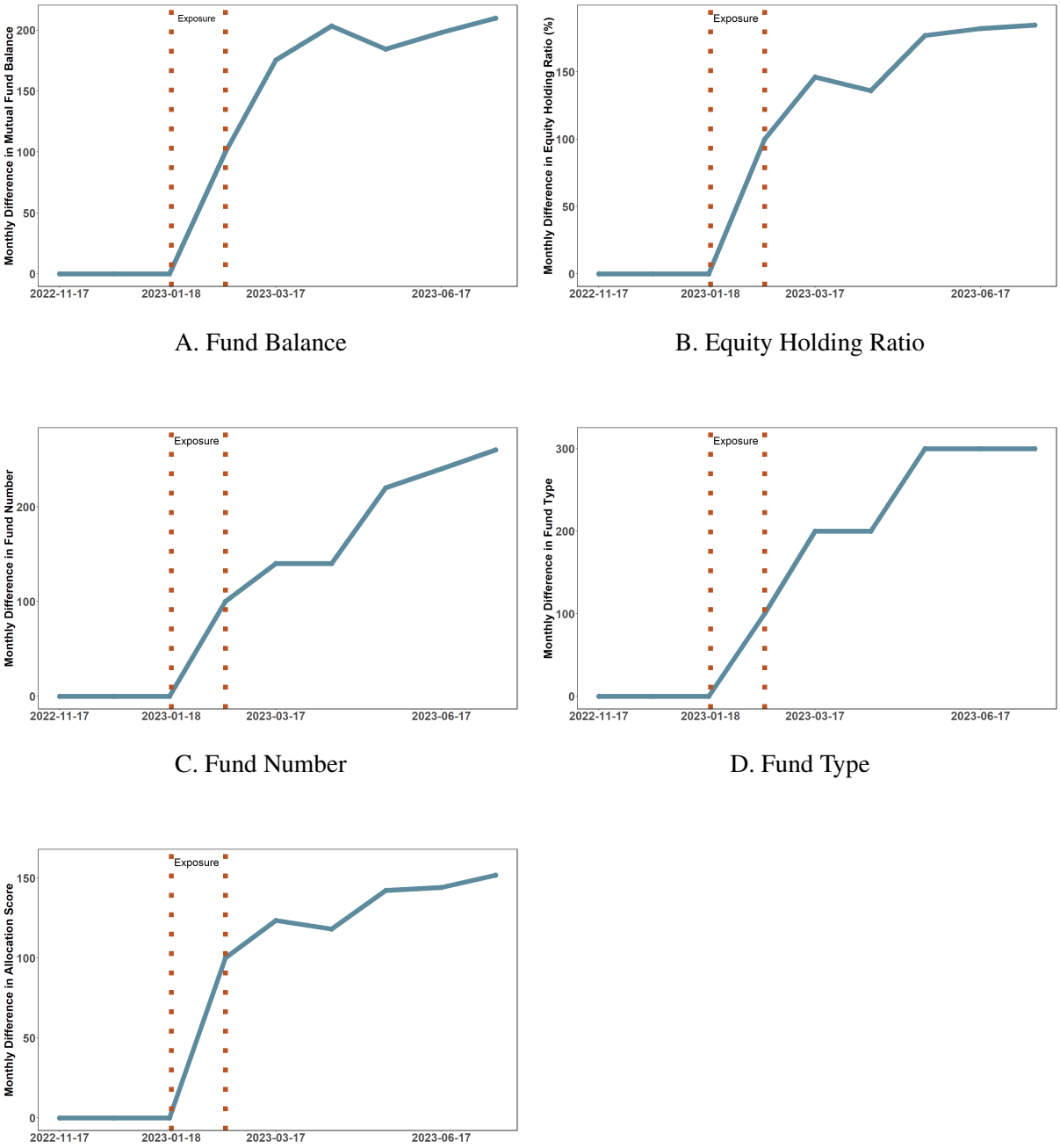
A. Timeline



B. Quasi-Experiment, Treated and Control Groups

Figure 2: Quasi-Experiment

This figure displays the timeline of the campaign starting on January 18^{th} (Panel A), as well as the quasi-empirical experiment, and the treated and control groups (Panel B).



A. Fund Balance

B. Equity Holding Ratio

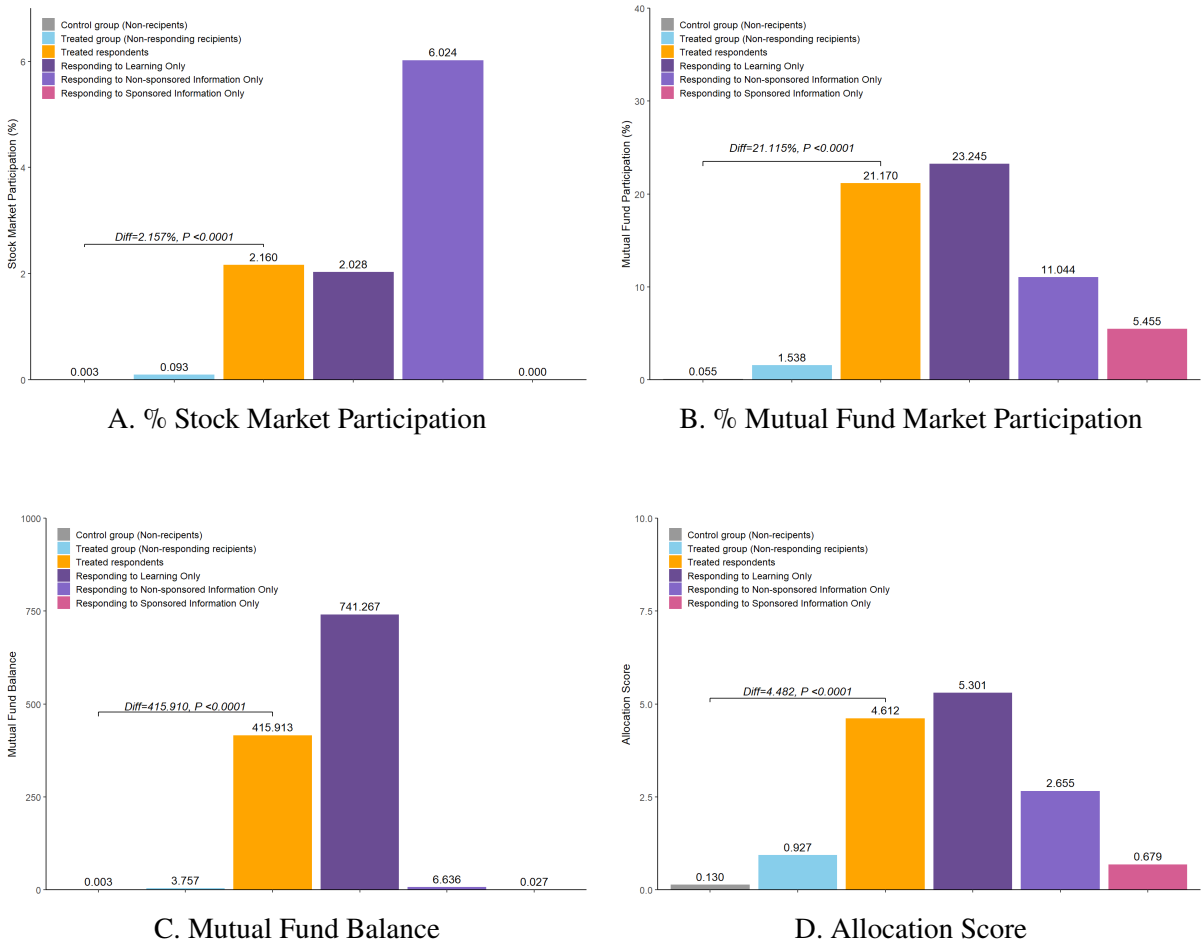
C. Fund Number

D. Fund Type

E. Allocation Score

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 *Fund Balance, Equity Holding Ratio, Fund Number, Fund Type, and Allocation Score* (Panel A-E). 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 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. % Stock Market Participation

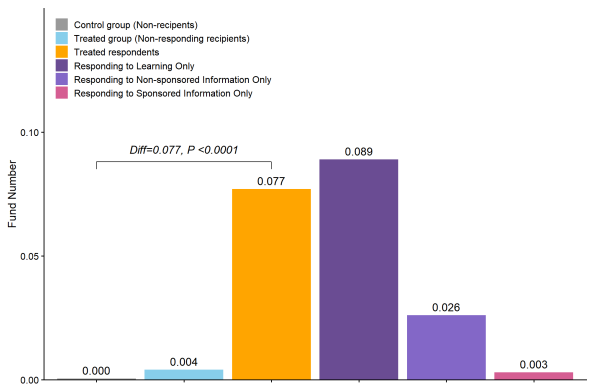
B. % Mutual Fund Market Participation

C. Mutual Fund Balance

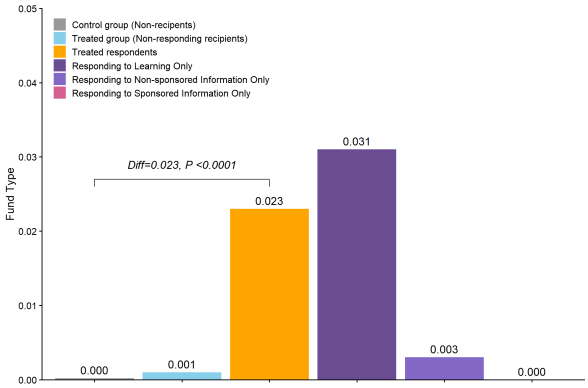
D. Allocation Score

Figure 4: Impact of Aggregate and Channel-Specific Platform Exposure: Treated Respondents

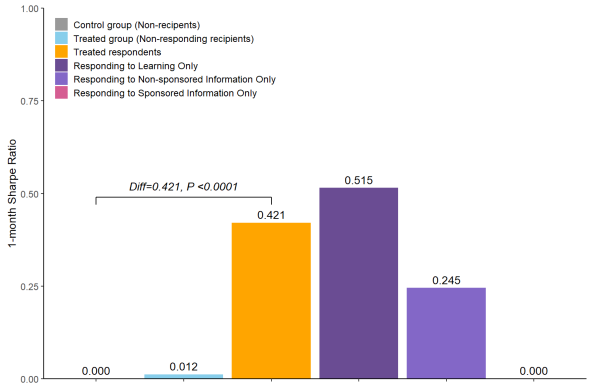
This figure display the impact of aggregate and channel-specific platform exposure on four key investment metrics: (1) capital market participation, measured using two binary indicators, (i) 'stock' is defined as individuals who have made any investment that includes equity exposure (i.e., investments 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 allocation score, fund number and fund type), and (4) risk-adjusted performance (measured by the Sharpe ratio) over 1-, 3-, 6-, and 9-month horizons (Panel A to J). Each bar represents one of the six groups: users in the control group (62,293 users), non-responding recipients in the treated group (60,994 users), treated respondents (1,299 users), and three subgroups of treated respondents who engaged exclusively with a single platform channel: learning-oriented (641 users), nonsponsored (498 users), and sponsored (55 users). "Diff" reports the difference in investment outcomes between the control group and treated respondents, along with the corresponding p-value.



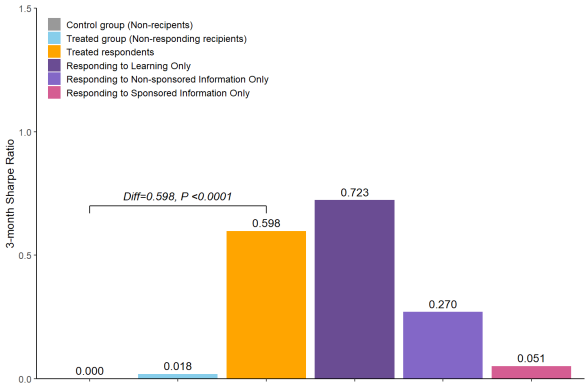
E. Fund Number



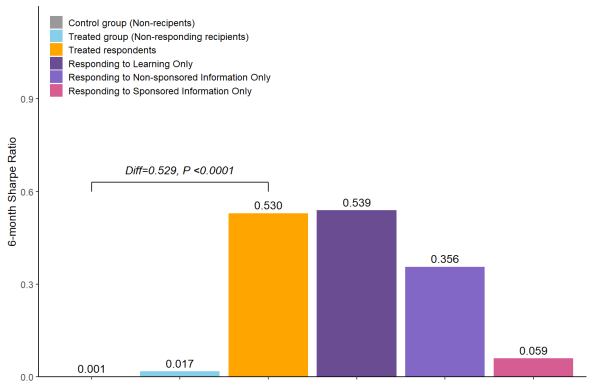
F. Fund Type



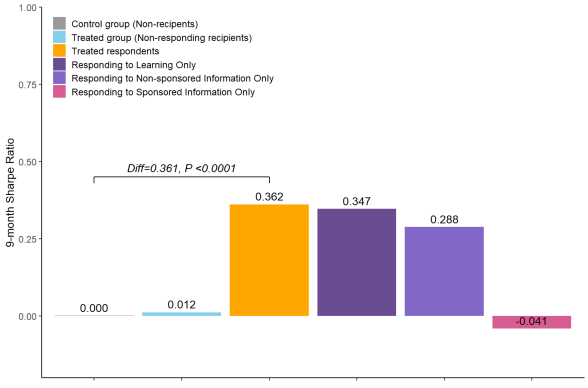
G. 1-month Sharpe ratio



H. 3-month Sharpe ratio



I. 6-month Sharpe ratio



J. 9-month Sharpe ratio

Figure 4: Impact of Aggregate and Channel-Specific Platform Exposure: Treated Respondents (Continued)

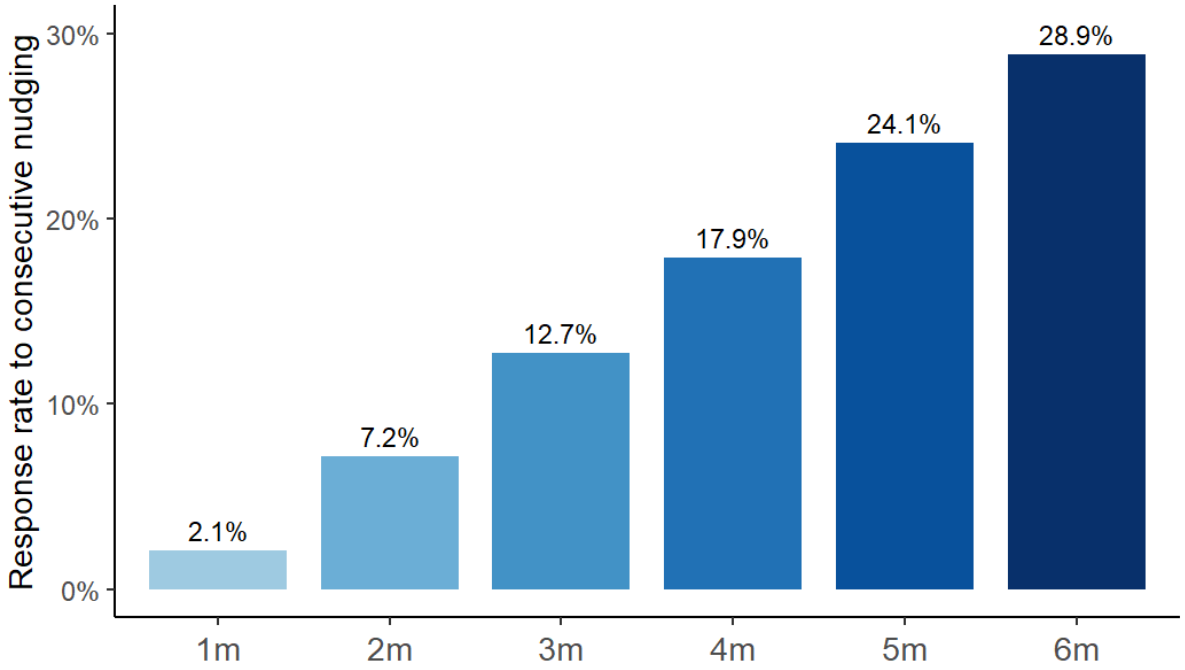


Figure 5: Response Rates to Digital Nudging Across Repeated Nudging Horizons

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.

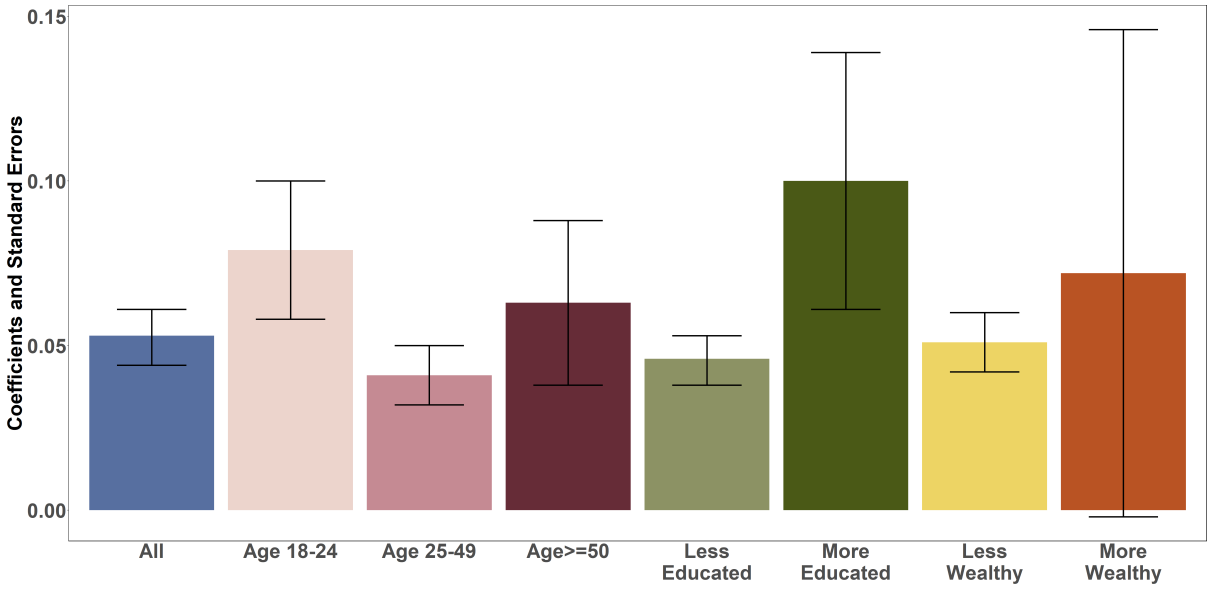
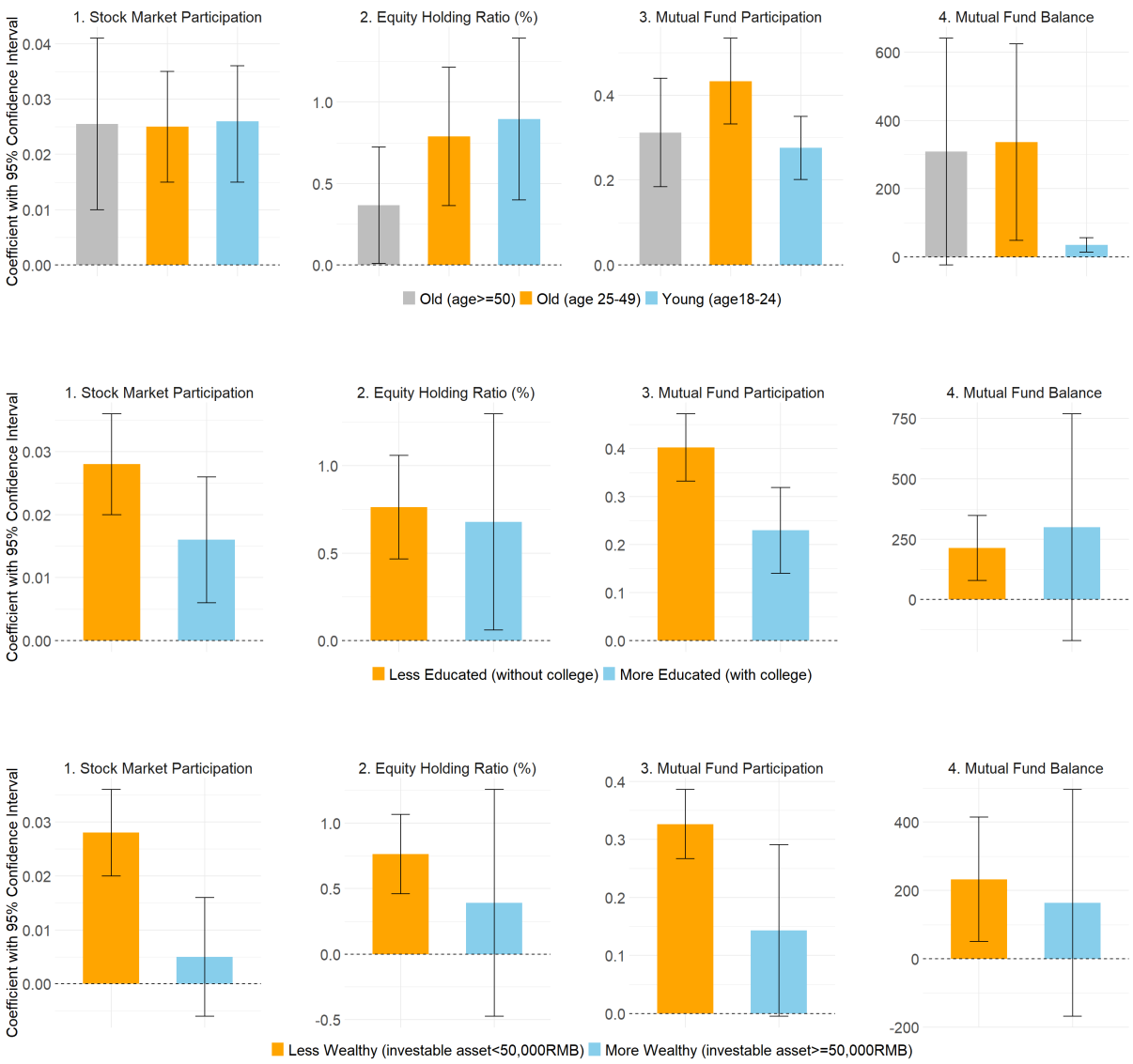


Figure 6: Heterogeneous Aggregate Platform Exposure (Intensive) Across Users' Characteristics

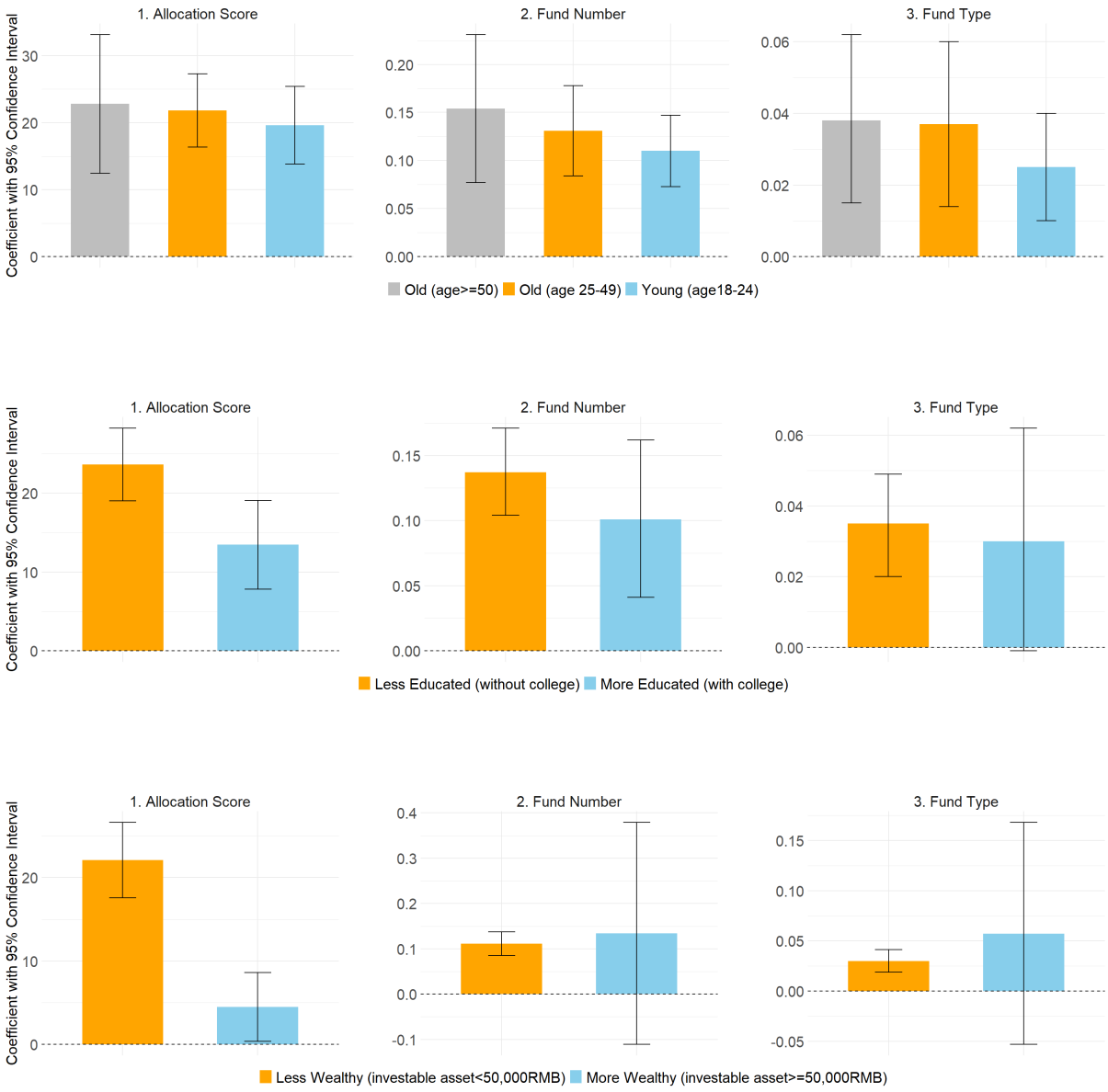
This figure reports the heterogeneous effect of digital prompts on the acquisition of aggregate platform exposure across various characteristics. The vertical axis represents the coefficient estimates and associated 95% confidence intervals of the first-stage regression model: $PlatformExposure_i = \alpha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

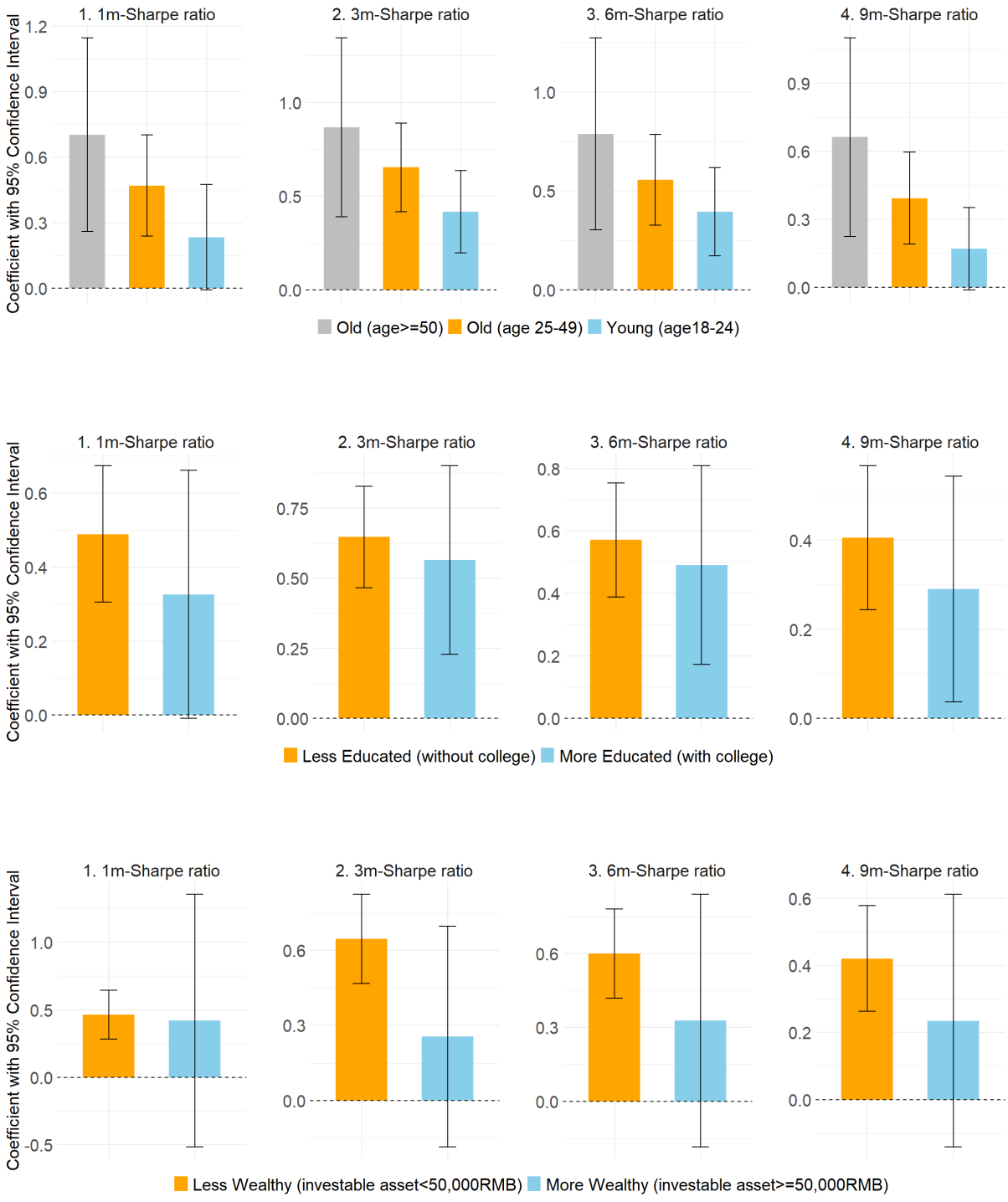
Figure 7: Heterogeneous Impact of Aggregate Platform Exposure Across Users' Characteristics

This figure illustrates the heterogeneous effect of aggregate 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 *Sharpe ratio* over 1-,3-, 6-, and 9-month horizons. 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 7: Heterogeneous Impact of Aggregate Platform Exposure Across Users' Characteristics (Continued)



Panel C. Investment Performance and Other

Figure 7: Heterogeneous Impact of Aggregate 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 Aggregate Platform Exposure

This table shows coefficient estimates and associated standard errors (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 aggregate platform exposure gained by the user i; and $\mathbb{1}\{PlatformExposure\}_i$ is a dummy variable equal to 1 if the user i engages with any digital financial services to acquire 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 prompts during the January campaign. Column (1) and (2) display the impact of the prompts on Platform Exposure$_i$ and $\mathbb{1}\{PlatformExposure\}_i$, respectively. We report 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***
	(0.004)	(0.001)
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 Aggregate Platform Exposure (Intensive) on Stock Market Participation

This table shows the coefficient estimates and associated standard errors (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 aggregate platform exposure on *D(Stock Market Participation)* and *Equity Holding Ratio* for treated and matched control users. Aggregate platform exposure is instrumented using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the prompts during the treatment. We report 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***
	(0.003)	(0.138)
Obs	124,586	124,586

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

This table shows the coefficient estimates and associated standard errors (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 five outcomes, each measuring the monthly average value during the treatment month: *Fund Balance*, *Fund Number*, *Fund Type*, and *Allocation Score*. These variables capture the average value of mutual fund balance, number of funds, distinct fund types, and portfolio allocation capability during the treatment month, respectively. We instrument aggregate platform exposure using $\mathbb{1}\{Nudge\}_i$, a binary variable set to 1 for users randomly assigned to receive the prompts during the treatment. We report 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	Allocation Score
	(1)	(2)	(3)	(4)
Platform Exposure$_i$	234.567***	0.129***	0.034***	21.319***
	(78.180)	(0.015)	(0.007)	(1.942)
Obs	124,586	123,686	123,438	123,688

Table 6: Second Stage - Effect of Aggregate Platform Exposure (Intensive) on Investment Performance

This table shows the coefficient estimates and associated standard errors (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 user i's annualized Sharpe ratio. The investor's Sharpe ratio is calculated using daily mutual fund portfolio returns over 1-month (Column 1), 3-month (Column 2), 6-month (Column 3), and 9-month (Column 4) periods following the treatment. For users with no mutual fund holdings, the Sharpe ratio is set to zero. Column (1)-(4) report the effect of aggregate platform exposure on 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 prompts during the campaign. We report standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	Annualized Sharpe ratio over			
	1-month	3-month	6-month	9-month
	(1)	(2)	(3)	(4)
Platform Exposure$_i$	0.456***	0.626***	0.551***	0.376***
	(0.083)	(0.082)	(0.081)	(0.070)
Obs	123,741	123,354	122,888	122,993

Table 7: Correlation Between Realized Outcomes and Channel-Specific Predicted Outcomes

This table reports the correlation between the realized investment outcome y and the predicted outcome $\hat{y}$ generated from 2SLS estimates of platform exposure to each information channel (learning-oriented, nonsponsored, and sponsored). The outcome y includes stock market participation, equity holding ratio, mutual fund balance, portfolio diversification (fund number, fund type, and allocation score), and risk-adjusted returns (annualized Sharpe ratio over 1-, 3-, 6-, and 9-month horizons).

	Platform Exposure	Learning-oriented	Nonsponsored	Sponsored
		(a)	(b)	(c)
	Correlation (outcome y and predicted y)			
D(Stock Market Participation)	0.0754***	0.1324***	0.0424***	-0.00004
Equity Holding Ratio	0.0351***	0.0900***	0.0111***	-0.0001
Fund Balance	0.0314***	0.0886***	0.0072***	-0.0001
Fund Number	0.1011***	0.1695***	0.0596***	-0.0004
Fund Type	0.0630***	0.1033***	0.0396***	-0.0003
Allocation Score	0.0683***	0.1063***	0.0428***	-0.0005
1-Month Sharpe ratio	0.0593***	0.0914***	0.0376***	-0.0004
3-Month Sharpe ratio	0.0547***	0.0953***	0.0314***	-0.0007
6-Month Sharpe ratio	0.0482***	0.0688***	0.0316***	0.0002
9-Month Sharpe ratio	0.0467***	0.0531***	0.0348***	-0.0004

Table 8: PCA Factor Loadings and Engagement Statistics Across Information Channels

This table reports the factor loadings from the principal component analysis (PCA) of the three information channels: a) learning-oriented; b) nonsponsored; and c) sponsored, along with descriptive statistics on user engagement with each channel. The factor loadings show the contribution of each channel to the first principal component, which summarizes the common structure of platform exposure. For each channel, we also report the number of treated users who engaged with the channel during the treatment month, and the mean and maximum interactive time (in seconds).

	PCA	Treated Respondents		
	Factor Loading	N	Mean (second)	Max (second)
Learning-oriented	0.7066	743	46	745
Nonsponsored	0.7070	601	106	2,036
Sponsored	0.0285	62	28	184

Table 9: 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 initiate investments, their investment amounts, and their cumulative gains. Col (1), "# recipients (no prior response)," shows the number of treated users who receive repeated nudging across the first to sixth months (1m–6m) but have 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 invest in mutual funds. Col (4), "Average Fund Balance," displays the average monthly mutual fund balance for the month in which the first response is made. Col (5), "1-month Sharpe ratio", is the annualized Sharpe ratio calculated over the one month following the initial response, and as explained in Eq. A1. Cols (6)-(8), respectively, list the annualized Sharpe ratios over the three-, six-, and nine-month horizons, corresponding to the month of the first response. Col (4)-(8) 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 users with at least one minute of aggregate platform exposure.

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

	# recipients (no prior response)	#1st-time respondents (%)	# Invested respondents(%)	Average Fund Balance	1-month Sharpe ratio	3-month Sharpe ratio	6-month Sharpe ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1m	62,293	2.09%	21%	1,965	3.84	3.92	2.84
2m	15,760	2.66%	26%	1,546	2.16	3.39	2.69
3m	8,443	3.21%	29%	252	6.45	2.56	1.05
4m	5,154	2.87%	31%	7,896	3.71	3.64	2.79
5m	3,226	3.16%	32%	179	4.82	3.32	3.60
6m	2,363	3.26%	22%	2,956	4.89	2.09	2.38

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

	# recipients (no prior response)	#1st-time respondents (%)	# Invested respondents(%)	Average Fund Balance	1-month Sharpe ratio	3-month Sharpe ratio	6-month Sharpe ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1m	62,293	0.60%	30.46%	3,438	4.75	4.27	3.44
2m	16,279	0.98%	31.88%	1,062	3.82	6.33	5.03
3m	9,035	1.07%	42.27%	778	6.21	3.33	1.43
4m	5,739	0.89%	43.14%	14,446	0.88	0.71	-0.42
5m	3,770	1.25%	31.91%	1,599	8.35	6.65	5.72
6m	2,867	1.60%	19.57%	6,938	6.38	5.82	4.54

A Internet Appendix

A.1 Detailed Descriptions for Allocation Score

Allocation Score is a score 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;

A.2 Measurement of Investment Performance

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

1) using an individual's daily mutual fund portfolio return over a 1-month (or 3-, 6-, and 9-month) period following the treatment to calculate the daily volatility;

2) Calculating the annualized Sharpe ratio of an individual's portfolio following the equation A1:

$$\text{Sharpe ratio}_{annualized} = \frac{(\overline{daily\quad return} - daily\quad deposit\quad rate) * \sqrt{252})}{\sqrt{daily\quad volatility}} \tag{A1}$$

where $\overline{daily\quad return}$ is the mean value of the daily portfolio return over a 1-month (or 3-, 6-, and 9-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.

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.

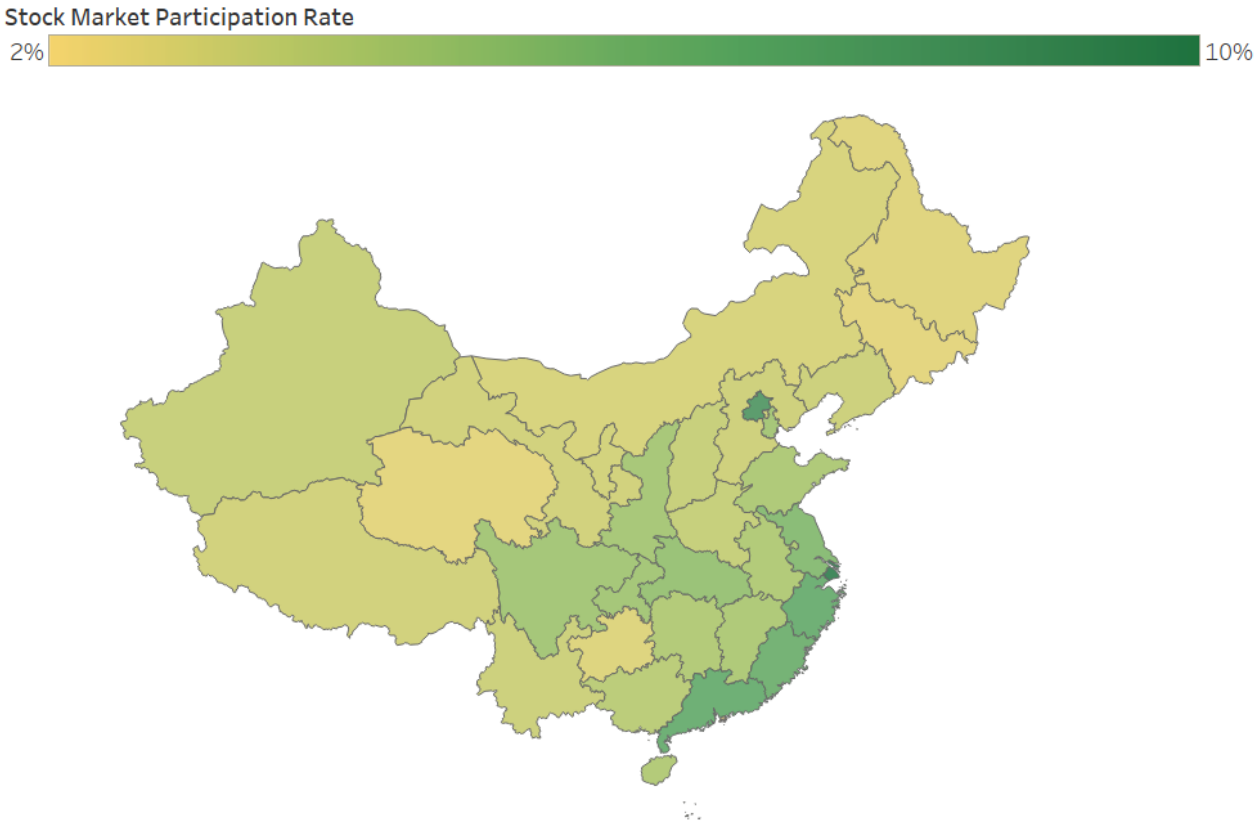
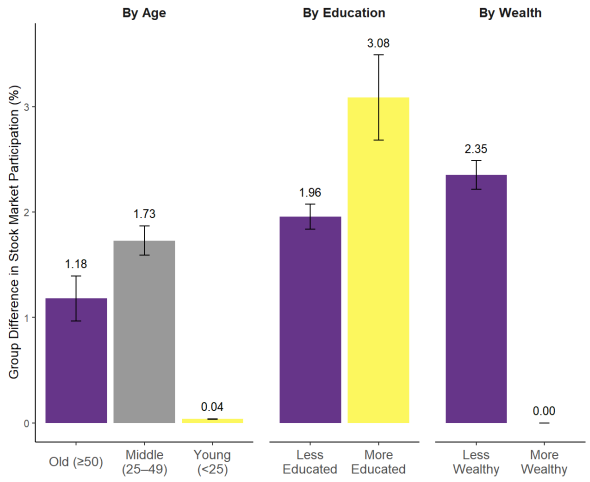
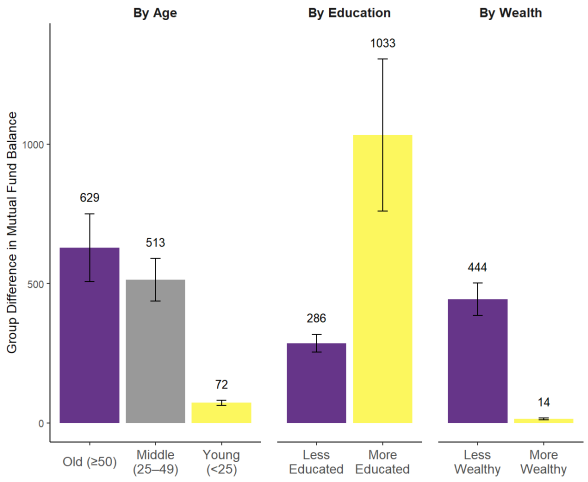


Figure A1: Stock Market Participation Rate of Platform Users

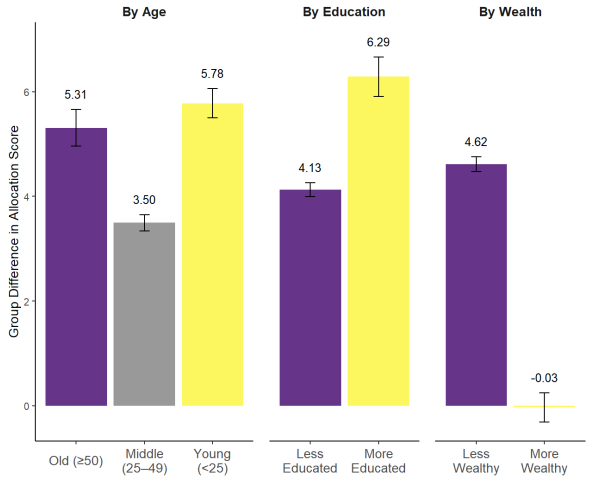
This figure shows the percentage of all platform users who participate in the Chinese stock market by making equity-exposed investments through the platform at the beginning of December 2022. Source: All calculations are based on data obtained from the platform we analyzed.



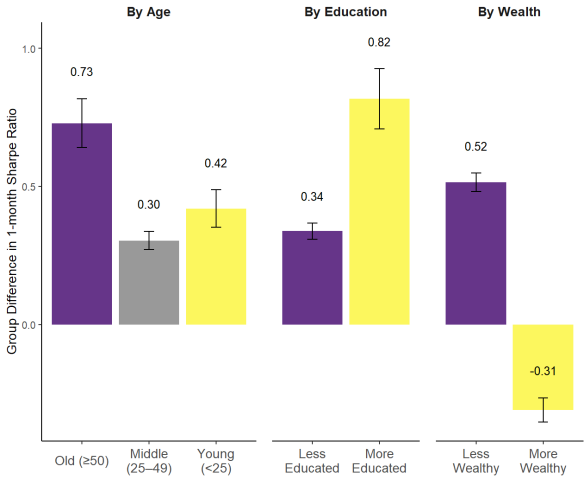
A. Stock Market Participation



B. Mutual Fund Investment



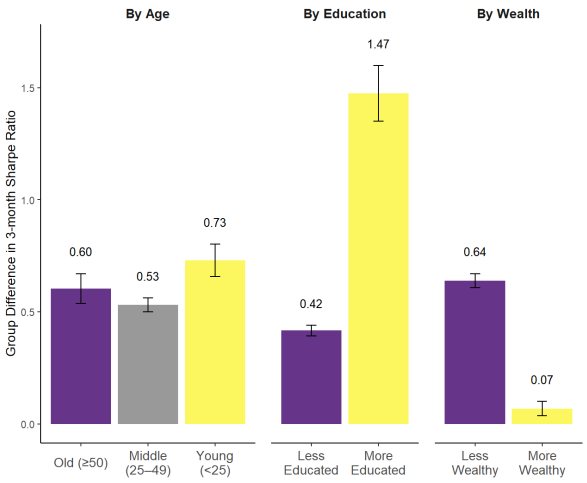
C. Portfolio Diversification



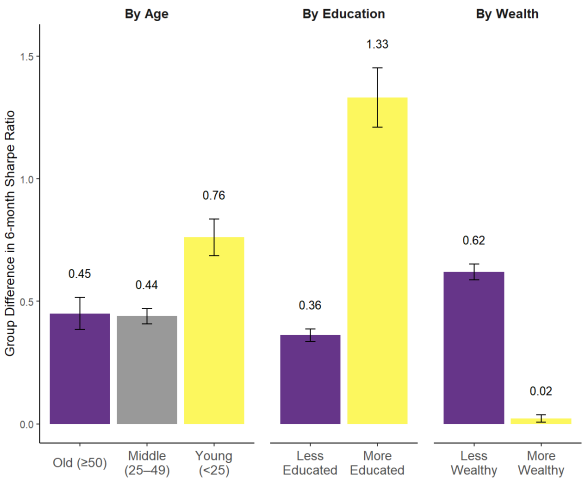
D. 1-Month Sharpe ratio

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

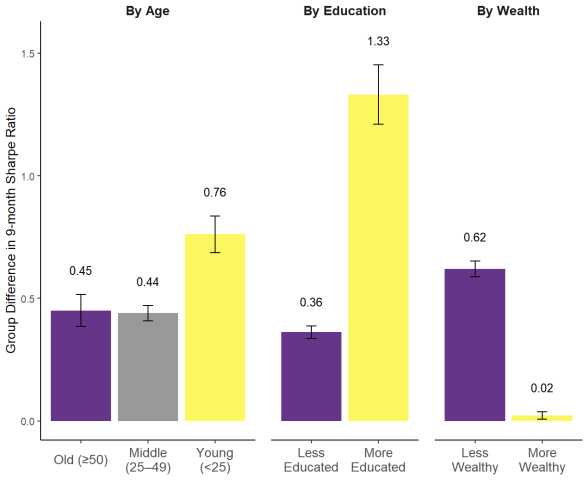
This figure displays the difference in means between non-recipients in the control group (62,293 users) and responding recipients in the treated group (1,299 users) for four investment outcomes: (1) stock market participation, (2) mutual fund balance, (3) portfolio diversification (measured by platform allocation score), and (4) risk-adjusted return (measured by the Sharpe ratio) over 1-, 3-, 6-, and 9-month horizons, in Panel A-G. Subgroup comparisons are presented across age (18–24, 25–49, ≥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 Sharpe ratio



F. 6-Month Sharpe ratio



G. 9-Month Sharpe ratio

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

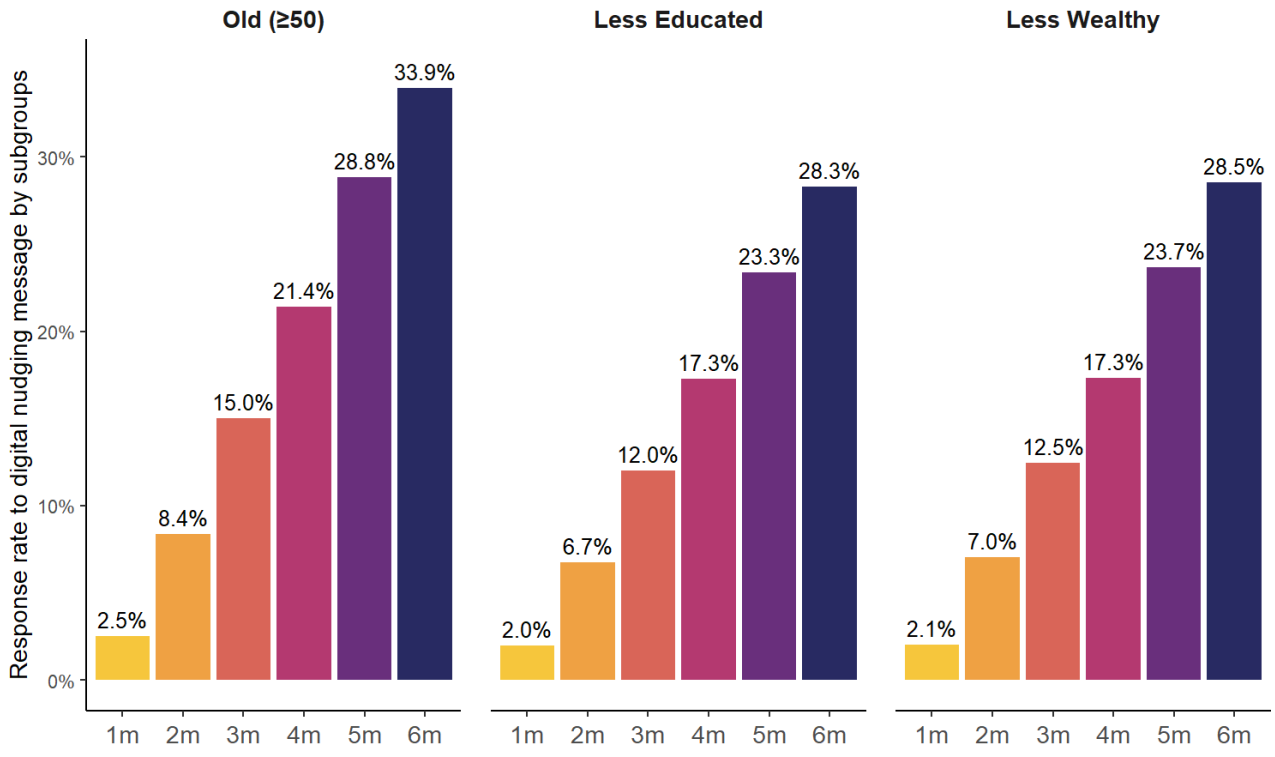


Figure A3: Response Rates of Older, Less educated, and Less Wealthy Across Repeated Nudging Horizons

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 Aggregate Platform Exposure (Extensive) on Stock Market Participation

This table shows the coefficient estimates and associated standard errors (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 aggregate 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 prompts during the treatment. We report 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***
	(0.007)	(0.328)
Obs	124,586	124,586

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

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

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

where Y_i represents one of five outcomes, each measuring the monthly average value during the treatment month: *Fund Balance*, *Fund Number*, *Fund Type*, and *Allocation Score*. These variables capture the average value of mutual fund balance, number of funds, distinct fund types, and portfolio allocation capability 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 prompts during the treatment. We report 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	Allocation Score
	(1)	(2)	(3)	(4)
$\mathbb{1}\{PlatformExposure\}_i$	608.091***	0.299***	0.075***	49.307***
	(197.835)	(0.025)	(0.014)	(1.801)
Obs	124,586	123,686	123,438	123,688

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

This table shows the coefficient estimates and associated standard errors (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 annualized Sharpe ratio. The investor's Sharpe ratio is calculated using daily mutual fund portfolio returns over 1-month (Column 1), 3-month (Column 2), 6-month (Column 3), and 9-month (Column 4) periods following the treatment. For users with no mutual fund holdings, the Sharpe ratio is set to zero. Column (1)-(4) report the effect of aggregate platform exposure on 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 prompts during the campaign. We report standard errors clustered at the individual level in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	Sharpe ratio			
	1-month	3-month	6-month	9-month
	(1)	(2)	(3)	(4)
$\mathbb{1}\{PlatformExposure\}_i$	1.058***	1.583***	1.405***	0.957***
	(0.175)	(0.162)	(0.174)	(0.163)
Obs	123,741	123,354	122,888	122,993

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 Sharpe ratio, (e) 3-month annualized Sharpe ratio, and (f) 6-month annualized 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 first-time respondents (n), the mean difference in the investment outcome between first-time treated 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 Sharpe ratio			3-month Sharpe ratio			6-month Sharpe ratio		
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	0.76	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 initiate investments, along with their investment amounts and cumulative gains. Col (1), "# recipients (no prior response)," shows the aggregate number of treated users who receive repeated nudging across the first to sixth months (1m–6m) but have 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 invest in mutual funds. Col (4), "Average Fund Balance," displays the average monthly mutual fund balance for the month in which the first response is made. Col (5), "1-month Sharpe ratio", is the annualized Sharpe ratio calculated over the one month following the initial response, and as explained in Eq. A1. Cols (6) and (7), respectively, list the 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	# Invested respondents(%)	Average Fund Balance	1-month Sharpe ratio	3-month Sharpe ratio	6-month Sharpe ratio
	(1)	(2)	(3)	(4)	(5)	(6)
All	2,316	24.22%	2,466	4.01	3.49	2.56
Old (>=50)	434	23.04%	5,755	5.26	3.63	2.67
Less Educated	1,929	23.54%	1,794	3.68	2.97	2.21
Less Wealthy	1,872	22.49%	2,335	4.70	3.76	2.87

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

This table shows coefficient estimates and associated standard errors (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 aggregate platform exposure gained by the user i. $\mathbb{1}\{Nudge\}_i$ is set to 1 for the users randomly assigned to receive the prompts during the January campaign. Column (1) and (2) display the impact of the prompts on Platform Exposure$_i$ following the Tobit and PPML model, respectively. We report 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***
	(0.600)	(0.473)
Adj R^2	0.070	0.001
Obs	124,586	124,586

Table A7: Robustness I (Difference Model): Second Stage - Effect of Aggregate Platform Exposure (Intensive) on Stock Market Participation

This table shows the coefficient estimates and associated standard errors (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 aggregate 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 prompts during the treatment. $\widehat{PlatformExposure_i}$ is estimated using the Tobit model (Panel A) and the PPML model (Panel B). We 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***
	(0.00001)	(0.001)
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***
	(0.003)	(0.126)
Obs	124,586	124,586

Table A8: Robustness I (Difference Model): Second Stage - Effect of Aggregate Platform Exposure (Intensive) on Investment Behaviors

This table shows the coefficient estimates and associated standard errors (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 five outcomes, each measuring the monthly average value during the treatment month: *Fund Balance*, *Fund Number*, *Fund Type*, and *Allocation Score*. These variables capture the average value of mutual fund balance, number of funds, distinct fund types, and portfolio allocation capability 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 prompts during the treatment. $\widehat{PlatformExposure_i}$ is estimated using the Tobit model (Panel A) and the PPML model (Panel B). We report 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	Allocation Score
	(1)	(2)	(3)	(4)
Platform Exposure$_i$	0.961***	0.0004***	0.0001***	0.067***
	(0.313)	(0.00003)	(0.00002)	(0.002)
Obs	124,586	123,686	123,438	123,688

Panel B. PPML Model

Dependent Var.	Fund Balance	Fund Number	Fund Type	Allocation Score
	(1)	(2)	(3)	(4)
Platform Exposure$_i$	234.567***	0.099***	0.024***	16.401***
	(76.408)	(0.008)	(0.004)	(0.367)
Obs	124,586	123,686	123,438	123,688