Beyond Performance: The Financial Education Role of Robo-Advising

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Abstract

Using proprietary individual investor account-level data obtained from Ant Group, we find that, in addition to providing investors better investment performance, robo-advising has a positive spillover effect on investor behavior. Specifically, after adopting robo-advising, investors have more diversified portfolios and exhibit reduced behavioral biases in portfolio management and fund choices in their self-directed accounts. To address concerns about self-selection during adoption, we use a randomized advertising program as the identification strategy, and our main findings remain robust. This effect is more prominent among adopters who were less sophisticated before the adoption. We highlight two features that strengthen the effectiveness of the robo-advisor in changing investor behavior: the continuous interactions between the robo-advisor and its adopters, and the accessibility of easy-to-apply educational resources.

1. Introduction

Over the past decade, as robo-advising has gained prominence, there has been a growing body of finance literature examining how robo-advising impacts investor welfare (e.g., D'Acunto et al., 2019; Rossi & Utkus, 2021; Bianchi & Brière, 2021). For instance, Rossi & Utkus (2021) document that robo-advising provides investors low-fee, diversified, and personalized portfolios with better performance than portfolios managed by investors themselves. Beyond this direct benefit, D'Acunto and Rossi (2023) point out that robo-advising has the potential to play a role of financial education, enhancing its adopters financial capabilities. Prior studies typically rely on the advised accounts of adopters to examine the consequences of robo-advising adoption. Therefore, it is challenging for these studies to discern the extent to which such consequences are attributed to the advice itself or to the educational effect. We address this empirical challenge by leveraging a proprietary dataset that includes not only adopters' advised accounts but also their self-directed accounts, both before and after the adoption. These self-directed accounts are not directly affected by robo-advice but can be influenced indirectly if investors learn from the advice. This setup enables us to empirically isolate the educational effect from the direct advising effect.

Our focus on the education effect is motivated by household finance literature, which underscores the importance of equipping households with financial knowledge and skills to make sound financial decisions (e.g., Campbell, 2006; Lusardi & Mitchell, 2014; Gomes et al., 2021). However, traditional financial education programs are expensive and not easily accessible for most households. By democratizing access to financial advisory services that used to primarily serve wealthier households, robo-advising may provide a cost-effective means of financial education for a broader spectrum of investors. Specifically, it leverages the information technology and automated algorithms to manage numerous small accounts with minimal human advisor involvement, resulting in significantly reduced advisory fees and lower account balance requirements. Beyond its cost-effectiveness, robo-advising can provide the financial knowledge and investment skills that many

investors seek. D'Acunto et al. (2019), for instance, proposed the possibility that their stock portfolio optimizer may operate as an "educational" tool to improve investors' financial literacy about risk and return, but they did not formally test it. In this study, we empirically investigate the educational effect of a Chinese robo-advisor, BangNiTou.

As the largest robo-advisor in China to date, BangNiTou (meaning "help you invest" in Chinese) is a joint venture between Ant group and Vanguard. Similar to Vanguard's DAS (Digital Advisor Service), BangNiTou provides advice on mutual fund portfolio management. It operates as a fully-delegated advisor, meaning that upon adoption, investors are not allowed to participate in any trading or rebalancing decision thereafter. BangNiTou provides no human advisory service. To partially fulfill the role of human advisors, it provides a service notes section that introduces and discusses a variety of financial concepts, principles and investment skills. Additionally, BangNiTou prepares and sends quarterly reports to update portfolio performance and explain its investment strategies to each of its adopters. Although these materials are designed to maintain client engagement, they may also help improve investors' financial literacy and investment ability.

Investors access BangNiTou primarily through Alipay, one of the top fintech platforms in China, as Ant Group, the owner of Alipay, has developed a smartphone app for BangNiTou and seamlessly integrated it into the Alipay app. A noteworthy feature of BangNiTou, aligning with our research objectives, is that it allows Alipay users to allocate a portion of their wealth to investments managed by BangNiTou (referred to as "BangNiTou portfolio" or "BangNiTou account" later in this study), while retaining the remainder of their wealth under their own direct management (referred to as the "self-directed portfolio" or "self-directed account" later in this study). We observe the education effect relying on the adopters' self-directed portfolios. Since BangNiTou cannot directly influence the self-directed accounts, we can attribute any improvement in investor behaviors observed through these accounts to the educational role of robo-advising.

We randomly select 100,000 investors from the population of approximately 1 million individuals who adopted BangNiTou between July 2020 and December 2020. We obtain robo-advising fund portfolio data, including trades and positions, at the individual investor account level from BangNiTou, and acquire self-directed fund portfolio data from Alipay, also at the individual investor account level. The sample period spans from July 2019 to March 2021. The control sample comprises investors who hold mutual fund portfolios in Alipay but have not adopted BangNiTou. Due to the substantial variation in individual characteristics among Alipay users, we use stratified sampling and the Propensity Score Matching (PSM) method to construct a control sample that closely matches the treatment group.

We first demonstrate that BangNiTou portfolios outperform adopters' self-directed portfolios by exhibiting a higher style-adjusted Sharpe ratio and lower style-adjusted volatility, consistent with the findings in Rossi and Utkus (2021).[1] BangNiTou portfolios also display fewer behavioral biases in portfolio management and fund choice than adopters' self-directed portfolios. The superior performance and reduced behavioral biases of BangNiTou portfolios lay foundation for the notion that investors can gain valuable benefits through learning from Robo-advising.

We then focus on the financial education role of robo-advising. Inspired by Calvet, Campbell, and Sodini (2009), we assess the educational effect from the perspective of investment behavioral biases. Behavioral finance literature indicates that individuals with limited financial knowledge tend to rely on heuristics in their decision-making, leading to more behavioral biases and, consequently, poorer investment performance.[2] If investors indeed learn from robo-advising, we expect a reduction in their behavioral biases following the adoption. Specifically, prior studies show that diversification is an essential contributing factor to the superior performance of robo-advising portfolio (e.g., Rossi and Utkus, 2021). Therefore, we examine whether investors learn from robo-advising on

[1] All the reported performance measures in this study are net of transaction fees.
[2] See Bailey, Kumar & Ng (2011), Barber & Odean (2013), Beshears et al. (2018) for more comprehensive reviews on retail investors' behavioral biases.

diversification. To comprehensively assess the learning effect, our analyses include several other well-established patterns of behavior biases in portfolio management and fund selection, including framing bias, tail return overweight, overextrapolation, and availability bias.

We document a substantial reduction in investors' behavioral biases in their self-directed portfolios following the adoption of BangNiTou. Specifically, investors hold more diversified fund portfolios and are less subject to framing bias, tail return overweight, overextrapolation, and availability bias after they adopt BangNiTou. Individual investor fixed effects are included in all specifications to control for time-invariant and unknown investor characteristics. The improvement in investor behaviors is economically significant, with some changes in measures amounting to as much as 15% to 20% of their pre-adoption standard deviation. Cross-sectional analyses show that the improvement in investor behaviors is more pronounced among investors exhibiting more pre-adoption behavioral biases.

The results discussed above cannot control for time-variant unobserved variables. For example, it is possible that robo-advising adopters may engage in other financial education programs that both enhance their financial sophistication and advise them to delegate investment to financial advisory services. In that case, our results could be driven by investors' changing financial sophistication resulting from other education programs. To address this concern related to unobserved time-variant variables, we use a BangNiTou promotional campaign, which randomly selects potential investors in the Alipay app and sends them pop-up ads, as our identification strategy. Specifically, we use exposure to the advertisement as an instrumental variable (IV) of robo-advising adoption. It is a valid IV in the sense that investors' exposure to the pop-up ads is random and the advertisement effectively converts more Alipay users into BangNiTou adopters. Our IV estimation results verify the effectiveness of robo-advising's financial education role, mitigating the concern that our findings are driven by the self-selection of investors with improved financial literacy.

We then examine the mechanisms through which BangNiTou improves investor behaviors. BangNiTou possesses several features that contribute to its effectiveness in changing investor behaviors. First, in contrast to the one-off interventions conducted in prior laboratory-based studies, investors' learning from such robo-advisors as BangNiTou is a continuous process. BangNiTou updates its portfolio performance on a daily basis, motivating its adopters to log in frequently to monitor their investments. These frequent logins repeatedly expose adopters to the educational resources within the BangNiTou app, including portfolio reports and service notes, strengthening the education effect of the robo-advisor. Second, existing literature point out that financial literacy programs including only financial content knowledge can barely change individual behaviors, because it is difficult for naïve investors to apply what they learn to subsequent investment decisions (Fernandes et al., 2014). In contrast, BangNiTou focuses on specific skills pertaining to fund portfolio management. Its advised portfolios serve as real models that allow investors to obtain real-world insights into fund selection, portfolio construction, and rebalancing. At the same time, its service notes explain the conceptual and theoretical foundations underlying the advised portfolios. The combination of these two components mirrors the common methodology in finance textbooks and classes: after introducing and explaining abstract concepts, practical examples are presented to illustrate how to apply them. The synergy enables investors with limited financial literacy to better apply what they learn into their portfolio decisions.

Using footprint data on investors' interaction with the BangNiTou app, we first find that the improvement in investor behaviors is significantly more prominent among investors who use the app more frequently or engage with it for longer durations. These investors tend to spend more time browsing the learning resources posted in the app that impart financial knowledge and investment skills, and thus are more likely to be influenced by the robo-advisor. This finding suggests that the repeated and continual interaction between investors and robo-advising enhances the education effect. Kaiser et al. (2022) find that the intensity of the treatment significantly influences the

education effect, and our results align with their conclusion. Second, we find evidence that the financial education effect of BangNiTou is magnified by its easy-to-apply learning materials. Our results show that the improvement in investor behaviors is most pronounced among adopters that both review BangNiTou portfolio reports and read more educational materials posted in service notes. In contrast, the effect is weaker when investors read less in the service notes section or do not review portfolio reports. These results are consistent with the notion that the interplay of setting real portfolio models and providing conceptual explanations of their underlying principles enables investors to effectively apply what they learn in practical investment scenarios.

Investors may learn from robo-advising by simply mimicking its advised portfolios without grasping the underlying conceptual foundations. To explore this possibility, we examine the extent to which adopters' self-directed portfolios deviate when they review BangNiTou portfolio reports. Our results show that investors who review BangNiTou portfolio reports purchase more funds included in their BangNiTou portfolios, allocate more investments to funds managed by the same fund companies featured in their BangNiTou portfolios, and divest more from funds reduced in their BangNiTou portfolios, and the overall style of their self-directed portfolios is more similar to that of robo-advising portfolios. These findings, taken together, suggest that adopters' self-directed portfolios are impacted by their BangNiTou portfolios. However, the economic magnitude of the impact is relatively small, implying that, on average, entirely replicating the robo-advisor's portfolios is unlikely to be a primary method through which adopters learn from the robo-advisor.

Finally, we observe that the enhancement in investor behaviors leads to improved performance. Based on their self-directed fund portfolios, we find that adopters achieve better performance in terms of style-adjusted Sharp ratio, portfolio return and volatility post-adoption, and the improvement in performance is significantly greater compared to non-adopters.

2. Related literature and contributions of this study

2.1 Robo-advising and investor welfare

There has been increasing research on the impact of robo-advising on investor welfare. The initial study by D'Acunto et al. (2019) explores how the introduction of an automated stock portfolio optimizer influences investors' portfolio choices and trading decisions. It documents that investors tend to diversify their stock portfolios more effectively after adopting robo-advising, and exhibit a reduction in a series of prominent behavioral biases, including the disposition bias, trend chasing, and the rank effect in their advised portfolios. The "portfolio optimizer" investigated by D'Acunto et al. (2019) functions more like a supplementary tool for investing, rather than providing investment and reblancing advice based on investor characteristics, as is the case with most robo-advisors. Ge et al. (2023) also explores the impact of such tool-based advisory services.

Rossi and Utkus (2021) examine Vanguard's Personal Advisor Service (PAS), a fully delegated robo-advisor that automatically allocates assets and rebalances portfolios based on algorithms designed according to adopters' characteristics. They find that PAS significantly improves investment performance, as measured by the abnormal Sharpe ratio, by constructing low-fee, diversified, and personalized portfolios. Furthermore, the improvement in investment performance is notably greater for investors with a low share of risky assets and limited investment experience before adopting robo-advising. Bianchi and Brière (2021) investigate a similar robo-advisor introduced by a French fund manager in a large set of employee saving plans. Unlike PAS, this service allows investors the discretion to follow or ignore advice offered by the robo-advisor. They observe that investors willing to rebalance their portfolios based on robo-advice achieve better investment performance.

Our study differs from existing research in several ways. First, all the aforementioned studies focus on the direct benefits of robo-advising, specifically the performance or behavioral improvements in advised accounts. In contrast, our paper focuses on the impact of adopting robo-advising on investors' self-directed investment accounts. Estimating this spillover effect is important for us to comprehensively understand the impact of robo-advising on investor wealth management,

particularly considering that the assets delegated to robo-advisors represent only a portion of investors' wealth.

Second, our study provides direct evidence on the role played by robo-advising in financial education. D'Acunto et al. (2019) and Bianchi and Brière (2021) both document improved investment performance and investor behaviors after the adoption of robo-advising. However, these improvements are observed in the advised accounts, so they may stem from either the advising effect or investors' learning effect or both, and it is difficult to disentangle one from the other.[3] In contrast, by tracking changes in the behavior and performance of self-directed accounts before and after adopting robo-advisory services, our paper effectively estimates the improvement in investor behaviors after they learn from BangNiTou, substantiating the role played by robo-advising in financial education.

Third, we conduct a comprehensive study on the impact of fully delegated robo-advisory services on small investors. Compared to other research samples, the BangNiTou service is accessible to a significantly broader spectrum of households, particularly those with lower incomes, as it requires an investment of merely RMB 800 (approximately $114). The low investment barrier of BangNiTou allows us to observe whether and how robo-advising can be beneficial to small investors who have little access to traditional financial advisory services. Additionally, considering the reluctance of small investors to adopt new technology (Campbell, 2006), and with only a fraction of their wealth delegated to the robo-advisor, this paper concurrently examine both advised accounts and self-directed accounts, enabling us to more comprehensively assess the welfare improvement effects of robo-advisory services on this demographic.

2.2 Financial education

[3] Robo-advisors vary in terms of investor discretion. Some robo-advisors offer advice to investors, allowing them the discretion to either accept or reject it, as exemplified by the robo-advisor in D'Acunto et al. (2019) and Bianchi and Brière (2021). For fully delegated robo-advisors (e.g., PAS and BangNiTou), the estimated performance and welfare improvements are primarily attributed to the advising effect. In this sense, the results of Rossi and Utkus (2021) provide a clean estimate of the impact of "advising" on investors' welfare.

Household finance literature documents that individuals with higher financial sophistication are more able to invest in capital markets, have high stock market participation (Van Rooij et al., 2011), more diversified portfolios (Calvet et al., 2007; Gaudecker, 2015), better portfolio rebalancing (Guiso & Vivano, 2015; Bianchi, 2018), and better investment performance (Gaudecker, 2015; Bianchi, 2018). As a result, both academic researchers and policymakers advocate for financial education to improve households' financial sophistication so that they can benefit from financial services (Lusardi et al., 2017; Gomes et al., 2021).

Although enormous resources have been directed into financial education in practice, academic evidence on the effectiveness of financial education is mixed. Some studies support the effectiveness of financial education in changing household saving behaviors (e.g., Drexler et al., 2014; Skimmyhorn, 2016; Song, 2015; Kaiser et al., 2022). Other studies cast doubt on the effectiveness of financial education in improving financial decision (Cole et al., 2011; Willis, 2013; Fernandes et al., 2014; Lusardi & Mitchell, 2014; Carpena et al., 2019).

Robo-advising is an educational platform that fits the features of effective financial education suggested by previous studies (e.g., Fernandes et al., 2014; Lusardi and Mitchell, 2014). First, the educational effect of robo-advising pertains to specific investment techniques rather than general financial knowledge, so it is easier for robo-advising adopters to directly apply what they learn into their investment decision-making processes. Second, robo-advising provides a "just-in-time" setting for us to observe any potential changes in investor behavior in real time. In our context, BangNiTou Adopters can promptly incorporate what they learn from the robo-advisor's educational resources into their self-directed portfolios, so the perceived relevance is high for its adopters. Third, robo-advising targets a specific group of individuals interested in acquiring investment skills rather than the general population. BangNiTou provides portfolio management knowledge and skills to Alipay users who have funds ready for investment and obviously have strong incentive to learn so as to improve their investment performance.

Furthermore, in this study, we highlight two key mechanisms that contribute to strengthening the financial education effect of robo-advising. First, unlike the traditional education programs that are often one-off intervention to investor literacy, the interaction between robo-advising and its adopters is continuous and repeated over time, and the education effect can be enhanced by such interaction. Second, the combination of robo-advisor portfolios, which set concrete models for investors to follow, and digital advisory services, which explain to investors the conceptual and theoretical foundation of portfolio management and fund choices, creates a synergy that facilitates investors to understand and apply what they learn from the robo-advising platform. These two mechanisms are costly for traditional education programs. However, by leveraging algorithms and information technology, robo-advising can provide them at a low cost to a large number of investors, particularly to young individuals and low-income households who desire financial knowledge but have limited access.

Our research is also motivated by Kaiser et al. (2022). They find that financial education can effectively improve investors' financial knowledge and downstream financial behaviors through a meta-analysis of 76 randomized experiments. Since most studies reviewed in their paper are experiments that rely on self-reported survey data, they call for future research to use administrative data to support the external validity of their conclusion.[4] Our study responds to this call by using large-sample, individual account-level data from a real investment platform, where investors are, unintentionally in most cases, exposed to financial education materials posted by the platform. Additionally, our study responds to the call made by Gomes et al. (2021) for future research on the design and cost efficiency of financial education interventions by exploring the possibility of leveraging robo-advising as an effective and affordable financial education tool for a broader base of investors.

[4] Kaiser et al. (2022, p.271) point out that "few studies can link their experiments to administrative data, so the usual caveats of having to rely on self-reported survey data also apply to these studies. Future research should aim to collect longer-run administrative data."

3. BangNiTou

BangNiTou is a joint venture of Vanguard and Ant Group; it was launched in April 2020. It is the Chinese counterpart of Vanguard's DAS, which was the world's largest robo-advisor as of the end of 2020. Ant Group operates Alipay, which was originally an online payment platform and is now the one-stop "super app" that integrate numerous apps into one platform serving everything in life, ranging from ride-sharing to utility bill payment to mutual fund investment. The BangNiTou app is integrated into the Alipay app, meaning that all of Alipay's one billion users can access BangNiTou simply through several clicks on their smartphones. Figure 1 presents the detailed steps by which Alipay users access BangNiTou in the Alipay app.

[Insert Figure 1 Here]

Similar to Vanguard's DAS (Digital Advisor Service), BangNiTou offers personalized portfolio strategies based on users' self-reported risk tolerance, demographic information and financial goals. Once users authorize the recommended strategy, it is automatically implemented by algorithms. BangNiTou operates as a fully-delegated advisor, meaning that investors are not allowed to involve in any trading or rebalancing decision once adopting the service. Yet investors have the flexibility to end the delegation whenever they want to manage investments by themselves. Throughout the delegation period, BangNiTou adopters receive quarterly updated reports on portfolio performance, allocation and rebalancing.

BangNiTou provides no human advisory service, and to partially fulfill the role played by human advisors, its app features a service notes section that post articles on a variety of financial knowledge and investment skills to improve the financial literacy of its users, so that they can better understand how the advised portfolios function and outperform their own portfolios. The BangNiTou Service notes comprise of three main sections: quarterly portfolio reports, investment philosophy, and market reviews. Quarterly portfolio reports summarize the performance of the portfolio over the quarter, analyze why the portfolio outperformed or underperformed, and explain how the portfolio

rebalance has been executed, as well as a letter from the chief investment officer of BangNiTou. The investment philosophy section primarily provides financial education materials, covering basic investment principles such as diversification, common pitfalls that investors may encounter, and behavioral biases investors often exhibit, such as extrapolation bias and the disposition effect. Market reviews regularly update comments about the market situation and help soothe investors' anxiety, stress, and depression after market turmoil to improve their mental well-being and avoid irrational trading, consistent with the survey result that investors hire financial advisors not only for higher returns but also to acquire peace of mind (Rossi and Utkus, 2020). Figure 2 presents more detailed examples of service notes in the BangNiTou app.

[Insert Figure 2 Here]

4. Data, sample and descriptive statistics

4.1 Data and sample

For the treatment group, we randomly select 100,000 BangNiTou adopters from the pool of approximately 1 million investors who signed up for BangNiTou between July 2020 and December 2020. For the control group, using stratified sampling based on demographic characteristics including gender, age, city tier of the investor's residence, and the amount of asset holdings, we select 300,000 investors from Alipay users that have purchased mutual fund though Alipay but have not adopt BangNiTou.[5] Then we construct a 1:1 control group using the Propensity Score Matching (PSM) method based on investor behavior characteristics.

Specifically, stratified sampling is conducted as follows. We label the number of BangNiTou adopters as of March 31, 2021, as M. We evenly distribute all the investors into 120 groups based on gender, age, city tier, and average wealth during April and June 2020 (two groups for gender, two groups for age, three groups for city tier, and ten groups for the amount of wealth). We then

[5] We use stratified sampling to secure a control group with demographic characteristics most similar to the treated investors. Alipay has a much broader client base than BangNiTou, with its users exhibiting diverse demographic and wealth attributes. It is possible that certain subsets of them are more likely to adopt BangNiTou, so we use stratified sampling to ensure an adequate representation in the control group investors for a more accurate match.

randomly select 100000/M×m_i adopters and 300000/ M×m_i non-adopters from group i, with i ranging from 1 to 120, and m_i representing the number of adopters (non-adopters) in group i.

To construct measures for investment behaviors, we require investors to have: (1) a minimum of three months of fund investment records, and (2) at least three transactions both before and after adopting the robo-advisor. After applying these criteria and dropping observations with missing control variables, our resulting sample comprises 74,090 adopters. Then we construct the control group by conducting PSM and selecting the most closely matched non-adopters from the pool of 300,000 Alipay users. The PSM is conducted based on a set of investor behavior characteristics over the 12 months before adopting BangNiTou, including asset value, style-adjusted portfolio return, style-adjusted portfolio volatility, style-adjusted Sharpe ratio, the proportion of money market funds, the proportion of equity funds, the proportion of bond funds, the proportion of index funds, the Herfindal index of the portfolio, the correlation of the fund return within the portfolio, portfolio return skewness, framing effect, extrapolation bias, availability bias, turnover, and trading frequency. The matching is done without replacement. The sample period is from July 1, 2019, to March 31, 2021. Definitions of variables are presented in the Appendix.

4.2 Descriptive statistics

Table 1 presents descriptive statistics for the characteristics of BangNiTou adopters during the 12 months before the adoption. Among the adopters, 29.6% are female, which is notably lower than the 47% of female investors in Vanguard's PAS. More than half (58.7%) of investors reside in the 14 top-tier cities. The mean (median) age is 30.84 (29), significantly younger than robo-advising adopters examined in prior studies. Over half of the adopters fall within the 25 to 35 age range.[6] The mean wealth for the BangNiTou adopters is RMB 67,665 ($10,572), which is substantially lower than the $588,246 mean wealth of Vanguard's PAS adopters. The adopters' median invested wealth

[6] The mean of adopter age is 63 in Rossi and Utkus (2021), 48 in Bianchi and Brière (2021), and 48 in D'Acunto et al. (2019), respectively.

is RMB 24,272 ($3,792), also considerably lower than the median invested wealth for Vanguard's PAS adopters ($282,450). Noted that the mean (median) wealth for robo-advising adopters in Reher and Sokolinski (2021) is $265,210 ($100,000), also significantly larger than the invested wealth in our study. Therefore, the robo-advising adopters in our study consist of younger investors with significantly less invested wealth.[7] Our findings demonstrate that investors become more sophisticated after interacting with the robo-advisor, and this hold even for those investors who are poorer and younger and previously have limited access to financial advisory services.

Table 1 also shows descriptive statistics of investment accounts for BangNiTou adopters before the adoption. More than 58% of their investments are allocated to money market funds (Yuebao in Aplipay) and wealth management products (WMPs), and mutual funds constitute approximately 40% of investment portfolios.[8] The monthly average investment in mutual funds is RMB 23,327 (equivalent to about US $3,332), and on average, they hold an average of 6.8 mutual funds. Among their fund holdings, 26.5% are in debt funds, 70.4% in equity funds, and 28.8% in index funds. The monthly average frequency of mutual fund subscription and redemption is 7.58. The monthly average amount of mutual fund subscription (redemption) is RMB 8,330 (RMB 6,595), and the average monthly turnover is 129.8%. These investment characteristics imply that investors tend to allocate more investment in low-risk instruments (including MMF and WMPs) and trade mutual funds frequently.

[Insert Table 1 Here]

Table 2 reports descriptive statistics on investors' self-directed accounts and BangNiTou portfolios (the accounts managed by the robo-advisor) during the eight months following the adoption. For the self-directed accounts, there is a substantial increase in the average investment to

[7] The average investment in the French robo-advisor studied in Bianchi and Brière (2021) was €36,140 (roughly US $39,393). The average investment in D'Acunto et al. (2019) was 1.1 million rupees (roughly US $14,300).
[8] Yuebao, operated by Ant Group, is the largest money market fund in China. Alipay users can easily invest in Yuebao with a few clicks in the smartphone app. Since Alipay penetrates into almost every household in China, Yuebao has an incredibly broad user base. WMP issued by commercial banks is an off-balance-sheet substitute for deposits that is widespread in China (Acharya et al, 2021). It offers investment returns and risks slightly higher than those of deposits yet much lower than those of mutual funds.

RMB 113,087 post-adoption, suggesting a general trend of Alipay users generally investing more through the Alipay app over the sample period, consistent with a broader trend that fintech giants are expanding their presence in household wealth management. Investors increase their mutual fund investment during the sample period, with the proportion of mutual fund holdings increasing from 39.7% to 47% and the number of funds invested rising from 6.78 to 12.46. The percentage of debt funds in total mutual fund investment drops to 15.1%, while equity funds see an increase to 80% of the total mutual fund investment. The proportion of index funds in total mutual fund investment drops slightly from 28.8% to 26.1%. In terms of trading activity, the monthly average frequency of fund subscription and redemption rises to 12.65, but the monthly average turnover decreases to 90.2%.

As to the delegated accounts, the mean (median) amount of investment is RMB 4,584 (RMB 1,026), equivalent to 6.45% (2.39%) of investors' total wealth in Alipay, suggesting that on average, investors regard BangNiTou as part of their portfolio and allocate only a small portion to it. The low investment in robo-advising portfolios could be attributed to a lack of trust, a factor that has been well-documented in prior studies as a key driver for the low-participation puzzle (Hong et al., 2004; Guiso et al, 2008; Hong et al., 2021). As many investors are unfamiliar with BangNiTou and have limited trust in the service, initially, they may choose to delegate only a small portion of their wealth to it.[9] In terms of account turnover, the median of BangNiTou account turnover is 44.7%, which is lower than the median of investors' self-directed account turnover (75.5%).

Table 2 also presents statistics regarding the interaction between BangNiTou and its adopters. The interaction is supposed to be most intense immediately following the adoption and subsequently decline gradually over time, so we first report statistics for the first month after adoption. The average duration of the time adopters spend in BangNiTou for the first month post adoption is 421

[9] Consistent with the trust explanation, investors gradually allocate more wealth into their robo-advising portfolios. As presented later in section 5.1, two thirds of adopters increase investment in BangNiTou within the 6 months after their first adoption, with the average amount of increased investment more than triple the initial investment.

seconds, and the average frequency of app logins is 43. Across all the sample period after the adoption, the average number of monthly BangNiTou app logins is 17, with the average duration of time spent in BangNiTou being 161 seconds per month. These statistics provide preliminary evidence indicating that adopters frequently log in and browse the content presented in the app. This ongoing learning process makes it possible for BangNiTou to influence investor behaviors.

[Insert Table 2 Here]

5. Main results

This section presents empirical results for both the direct and spillover effects of robo-advising. For the direct effect, we primarily show that robo-advising portfolios outperform investors' self-directed fund portfolios, laying the foundation for the idea that investors can learn from robo-advising for better portfolio management. We then focus on the spillover effect, specifically the educational effect of robo-advising.

5.1 **The direct effect of robo-advising**

5.1.1 The performance of Robo-advising portfolios

We investigate whether BangNiTou portfolios outperform adopters' self-directed fund portfolios, both pre and post BangNiTou adoption. We evaluate performance from three dimensions: investment return, volatility, and the Sharpe ratio. All measures are derived from individual account data and aggregated at the monthly level. Volatility is the standard deviation of portfolio daily return for the month. The Sharpe ratio is the monthly average of daily returns divided by daily return volatility of the same month. Because investment performance varies with portfolio styles and over time, we rely on style-adjusted measures to exclude the effect of time and portfolio style. The style-adjusted return/volatility/Sharpe ratio is defined as the portfolio's raw value of return/volatility/Sharpe ratio minus the portfolio style return/volatility/Sharpe ratio. To compute style measures, we follow a two-step process. First, we calculate the market-wide average performance for equity funds and debt funds, respectively. Second, the benchmark performance for the style is

determined as the weighted-average performance of the debt and equity fund portfolios, with the weighting based on the proportion of equity versus debt in the investor's portfolio.

Table 3 presents the style-adjusted performance measures for BangNiTou accounts and investor self-directed accounts during the windows of [-12, -1] and [1, 8], with 0 representing the month of robo-advising adoption. The significantly negative style-adjusted Sharpe ratios of investors' self-directed accounts for both pre- and post-adoption periods indicate that, on average, investors' self-directed portfolios perform worse than the market. In contrast, the average style-adjusted Sharpe ratio of BangNiTou accounts is significantly positive and larger than that of self-directed accounts. In our sample, 60% (65%) of robo-advising accounts outperform investors' self-directed accounts of the same period (of the period before adoption), suggesting that the robo-advisor effectively improves investors' portfolio performance, and investors can benefit from delegating asset management to the robo-advisor. The style-adjusted return of the robo-advising portfolio is higher than that of the self-directed portfolio before robo-advising adoption but lower than the self-directed portfolio of the same period. The style-adjusted volatility of the robo-advising portfolio is significantly lower than that of the self-directed portfolio both before and after adoption, indicating that BangNiTou enhances Sharpe ratio primarily by reducing portfolio volatility rather than by increasing returns. These findings echo and reinforce the conclusion of Rossi and Utkus (2021) by demonstrating that robo-advising portfolios outperform investors' self-directed portfolios both before adoption and of the same period. The economic magnitude of the improvement in performance is also large, with the monthly average Sharpe ratio increasing from −0.049 (before adoption) to 0.041 (after adoption).

[Insert Table 3 Here]

Figure 3 depicts the trend in portfolio performance for BangNiTou accounts and investors' self-directed accounts over the period of twelve months before and eight months after the adoption. Time "0" represents the month when clients adopt the robo-advisor. The style-adjusted Sharpe ratio of

BangNiTou portfolios consistently surpasses that of adopters' self-directed portfolios in almost every month post adoption.[10] The style-adjusted volatility of BangNiTou portfolios is lower than that of adopters' self-directed accounts in almost every month after adoption, but investment return of the robo-advising portfolios is generally lower than that of the adopters' self-directed portfolios, reinforcing our conclusion that BangNiTou improves investment performance primarily by reducing portfolio volatility and achieving a better risk-return balance, rather than through a higher portfolio return.

[Insert Figure 3 Here]

The superior performance of BangNiTou portfolios persuades investors to allocate more investment to their robo-advising accounts. In our sample, 51.9% adopters increase investment in their robo-advising portfolios within three months after the initial adoption. On average, the increased amount is RMB 8,300, equivalent to 331.1% of their initial investment in BangNiTou. Within six months after adoption, the percentage of adopters increasing their investments in BangNiTou portfolios rises to 66.9%, with an average increased investment of RMB 9,573, equivalent to 374.8% of their initial investment in BangNiTou.[11] These statistics suggest that investors learn about the robo-advisor's ability to perform portfolio management gradually after adopting and interacting with it. As demonstrated in Greig et al. (2023), the learning process of investors updates their understanding of robo-advising over time, making them more willing to invest in robo-advising. Trust may be another reason for the increased investment.

5.1.2 Robo-advising and investor behavioral biases

Robo-advising manages portfolios through algorithms and is designed to avoid behavioral biases. In this section, we use robo-advising portfolios as the benchmark to investigates the extent to

[10] The negative style-adjusted return of robo-advisor portfolios in month "0" mainly results from the one-time deduction of transaction costs when constructing portfolios.

[11] These statistics include automatic investment plan (AIP). Statistics excluding AIP are similar, with 51.0% (66.0%) adopters increasing investment in their robo-advising portfolios within three (six) months after the adoption. The mean of increased amount within three (six) months after adoption is RMB 8,236 (9,353), equivalent to 325.0% (361.5%) of their initial investment in BangNiTou.

which individual investors are subject to behavioral biases. Our analyses focus on behavioral biases in portfolio management and fund choices, as these two aspects are more likely to be improved by the robo-advisor and less subject to investor discretion.[12]

Prior literature documents that individual investors tend to underdiversify their portfolios (e.g., Goetzmann & Kumar, 2008). We measure the extent of diversification of the fund portfolio using the Herfindal index and the fund return correlation. Specifically, if the ratio between the value of the mutual fund i and the total value of the fund portfolio is λ_i, the Herfindal index (HHI) of the portfolio is $\sum_{i=1}^{N} \lambda_i^2$. The average fund return correlation is constructed as follows: we first calculate the Spearman correlation between each fund and the whole portfolio using daily returns in a given month and then use the weighted-average correlation for all funds in the portfolio as the correlation measure for the portfolio. The higher the correlation measure, the less diversified the portfolio is.

Framing bias refers to the pattern that investors buy and sell individual assets without considering the effect on their total portfolio (Bailey, Kumar & Ng, 2011). Following Bailey et al. (2011), we measure the monthly framing bias as 1 minus the ratio of trading frequency to the number of days with trading for the month. The higher the measure, the more likely investors trade a single asset in a given day and the higher the framing bias.

Our analysis includes three specific behavioral biases in fund choices, including availability bias or limited attention (Barber & Odean, 2008; Barber et al., 2021), extrapolation bias (Greenwood & Shleifer, 2014; Da et al., 2021) and tail returns overweight (Kumar, 2009). Availability bias or limited attention refers to the pattern that investors favor assets that are attention-grabbing, such as

[12] Bailey et al. (2012) investigates individual investors' behavioral biases in mutual fund investment. Barber and Odean (2013) review research on individual investor behavioral biases. Beshears et al. (2018) review household finance literature related to behavioral biases. These studies reveal that behavioral bias leads to trading loss, and includes a disposition effect (Odean, 1998), overtrading (Barber & Odean, 2000), underdiversification (Goetzmann & Kumar, 2008), attention-grabbing trades (Seasholes & Wu, 2007; Barber et al., 2021), overextrapolation bias (Greenwood & Shleifer, 2014; Da et al., 2021), and tail returns overweight (or preference for a lottery-type asset) (Kumar, 2009; Akbas and Genc, 2018; Clifford et al., 2021). A Vanguard report suggests that eliminating behavioral biases contributes to a 50% increase in net returns (Kinniry et al., 2014). We did not focus on disposition effect and overtrading, because BangNiTou does not directly advise on these two behaviors and adopters have the discretion to quit and repurchase the service at any time. In the untabulated results, we also find evidence that investors lower their trading frequency after robo-advising adoption.

mutual funds with high returns or turnover over the recent past and funds that are heavily advertised. We define a fund to be attention-grabbing if it ranks in top 10% for performance over the last month or is in the top 10% of subscriptions over the last month. Extrapolation bias is the tendency to take a project recent experiences into the future and buy mutual funds that have outperformed in the recent past. We measure extrapolation bias as the percentage of the value of recently outperforming mutual funds (ranked in the top 20% of mutual funds of the same style over the past 12 months) in the value of total funds purchased in the month. The higher the measure, the stronger the extrapolation bias. Tail return overweight refers to the tendency to overweight the probability of extreme positive returns and therefore, prefer mutual funds with positively skewed returns. We first calculate the lottery score over the last six months for each mutual fund following the method described by Han and Kumar (2013) and then use the value-weighted average lottery score for all mutual funds in the portfolio as our measure of the investor's tail return overweight. The higher the measure, the stronger the tendency to overweight tail returns.

Figure 4 presents the differences in behavioral bias measures between robo-advising portfolios and the adopters' self-directed portfolios during the same period. The robo-advisor displays fewer behavioral biases in all dimensions presented in the figure, including availability bias, extrapolation bias, tail return overweight, framing bias, and underdiversification, with the difference more prominent in availability bias, extrapolation bias, and framing bias. BangNiTou portfolio HHI and fund return correlation are significantly lower than the adopters' self-directed portfolios, suggesting that investors underdiversify their investments, consistent with the findings of prior literature that financial advisory firms contribute to individual investors' portfolio diversification (Shapira & Venezia, 2001; Kramer, 2012; Hoechles et al., 2017; D'Acunto et al., 2019). In the untabulated results, we find that before adopting robo-advising, investors who exhibit more pronounced behavioral biases experience significantly worse performance, supporting the notion that investors can enhance their investment performance by acquiring skills to mitigate these behavioral biases.

[Insert Figure 4 Here]

5.2 **The financial education effect of robo-advising**

5.2.1 Regression model

We examine the education effect in two steps. First, we analyze the effect using only the sample of investors who adopt robo-advising. The regression model is as follows:

$$DepVar_{i,period} = a + \beta post_i + \gamma control_{i,period} + v_i + e_{i,period}. \quad (1)$$

The dependent variables are measures of behavioral biases in fund choice and portfolio management.[13] Individual investor fixed effects are included to control for time-invariant unobserved individual investor heterogeneity. The variable of interest is *post*, equal to 1 for observations after the robo-advisor sign-up, and 0 otherwise.

Second, we use a DID research design to examine the financial education effect on adopters relative to the control group. For details on the control group construction please refer to the data and sample in Section 4. The regression model is as follows:

$$DepVar_{i,period} = a + \beta_1 post_i + \beta_2 Treat_i \times post_i + \gamma control_{i,period} + v_i + e_{i,period}. \quad (2)$$

Treat is defined as 1 for investors who adopt robo-advising, and 0 otherwise. *Post* is defined the same as in equation (1). The variable of interest is the interaction term $Treat_i \times post_i$, which captures the additional effect of robo-advising on investor behaviors. This specification further controls for factors that affect both the treatment and control groups. Individual investor fixed effects are included in all specifications. For portfolio underdiversification, we use two measures, specifically the Herfindal index and the average fund return correlation as the dependent variables, respectively. The other four dimensions of investor behavioral biases are framing bias, tail return overweight, extrapolation bias, and availability bias. The size of invested wealth, style-adjusted portfolio return, style-adjusted volatility, the share of equity funds in invested wealth and portfolio

[13] The monthly observations used in the previous sections of the study are averaged at the investor-period level for this specification. In this study, we calculate measures of investor behavioral biases at the investor-period level, because the calculation of such measures typically demands a relatively long time period (at least three months). Consequently, we also adjust the other variables into investor-period level observations to maintain consistency.

turnover are included as control variables for all specifications. When one aspect of behavioral bias is examined, all the other behavioral bias measures are included as control variables.

5.2.2 Empirical results

We begin by examining what determines investors' decisions to adopt robo-advising, and the results are presented in Table 4 Column (1). Probit model is used in this table. The dependent variable is whether the investor signs up for BangNiTou. Independent variables include a set of investor and portfolio characteristics within the 12 months preceding the adoption. Note that demographic characteristics, such as gender, age, and city of residence that may affect investors' decisions are not included in this specification, because they have been used in the stratified sampling, making it unfeasible to analyze them in the determination test.

As reported in Table 4 Column (1), investors with better self-directed mutual fund portfolio performance (higher style-adjusted Sharpe ratio and portfolio return and lower style-adjusted portfolio return volatility) are more likely to adopt robo-advising. Investors allocating more wealth to MMF and WMPs and less into risky assets are more likely to adopt robo-advising. Investors who have more diversified mutual fund portfolios (lower portfolio HHI and average return correlation) and invest more in index fund are more willing to adopt robo-advising. Investors who have less framing bias, extrapolation bias, and availability bias are more likely to adopt robo-advising. Collectively, these findings suggest that investors with better mutual fund performance, low risk preference, and fewer behavioral biases are more likely to adopt robo-advising. Additionally, investors who trade more frequently and display more tail return overweight are more likely to adopt robo-advising.[14]

[Insert Table 4 Here]

[14] Contrary to our findings, Rossi and Utkus (2021) document that investors with poorer self-directed account performance are more likely to adopt robo-advising. Additionally, Reher and Sun (2019) find that investors who underdiversify their portfolios ex ante are more likely to adopt robo-advising. Discrepancies in investor demographic characteristics may be one possible explanation for these varying results. Most robo-advising adopters in Rossi and Utkus (2021), for instance, were previously clients of traditional financial advisory who are wealthier investors with more investment experience and sophistication. By contrast, BangNiTou is integrated into the Alipay app—the super app that has about 1 billion Chinese users and penetrates almost every household in China—and thus is accessible to a much broader client base containing numerous poorer and younger investors who have limited financial knowledge.

Table 4 Column (2) presents regression result of the same model as in Column (1) but using the matched sample. Most independent variables are insignificant, suggesting that the adopters and non-adopters are similar in terms of their investment behavior characteristics after the matching process.

Table 5 reports regression results for the robo-advising's impact on investor behavioral biases in portfolio management. Individual investor fixed effects are included in all specifications. The coefficients of $post_i$ in Columns (1), (3), and (5) are significantly negative, indicating that the adopters' mutual fund portfolios become more diversified and display reduced framing bias after the adoption. The significantly negative coefficients of the interaction term $Treat_i \times post_i$ in Column (2), (4), and (6) suggest that compared to the control group of non-adopters, investors' portfolios are more diversified and display less framing bias after adopting robo-advising.

In terms of the economic magnitude of the education effect, the coefficient of $Treat_i \times post_i$ in Column (2) is -0.051 (significant at the 1% level), meaning that after controlling for other variables, the adoption of robo-advising results in a 5.1% decrease in the Herfindal index of the adopter's self-directed portfolio, equivalent to 0.2 standard deviations of the Herfindal index. According to the thresholds proposed by Kraft (2020), where less than 0.05 standard deviation is small, 0.05 to less than 0.20 is medium, and 0.20 or greater is large, the economic magnitude of the effect on diversification is large. The size of the effect on framing bias is medium, equivalent to 0.15 standard deviations of the level before adopting robo-advising.

[Insert Table 5 Here]

Table 6 reports regression results for investor behavioral biases in fund choices. Columns (1) and (2) present results for tail return overweight. Although the coefficient of *post* is significantly positive in both columns, the coefficient of $Treat_i \times post_i$ in Column (2) is significantly negative, suggesting that compared to the non-adopters, robo-advising adopters are less subject to tail return overweight post adoption. The changes in extrapolation bias are similar. Investors display reduced availability bias after adopting robo-advising, and the reduction is still significant when compared

with the non-adopters. Collectively, the evidence in this section suggests that the robo-advisor effectively mitigates investor behavioral biases after they adopt and interact with the robo-advisor.

[Insert Table 6 Here]

In terms of the economic significance, as depicted in Figure 5, the educational effects on behavioral biases in fund choices generally lower than that on portfolio management (including underdiversification and framing effect). Specifically, the effects amount to 5.96% of the standard deviation for availability bias, 1.85% for tail return overweight, and 2.59% for extrapolation bias. One explanation for the discrepancy is that the education effect on investors' behavioral biases in fund choices could be mitigated by brokers' marketing strategies. Brokers might exploit investor behavioral biases in fund choices to maximize their own sales rather than making efforts to alleviate these biases. For instance, brokers recognizing the presence of extrapolation bias might promote more funds with impressive recent performance records to investors.

[Insert Figure 5 Here]

Next, we explore how the education effect of robo-advising on investor behavior varies with investors' ex ante sophistication and report results in Table 7. Inspired by Calvet, Campbell, and Sodini (2009), we construct a measure of investor sophistication based on their trading behaviors before robo-advising adoption. The rationale is that the more behavioral bias investors exhibit in portfolio management and fund selection, the less sophisticated they are. Specifically, for each of the six behavior bias measures as presented in Figure 4, we divide all adopters evenly into 5 groups according to the extent of behavioral bias, with the score of 5 assigned to those in the highest group and the score of 1 to those in the lowest group. Our measure of sophistication, *Sophisitication score*, is the average score across these six behavioral bias measures for the investor.

The variable of interest is the interaction term of *Post* and *Sophistication score*. As reported in Table 7, the coefficients of *Post* Sophistication score* are significantly negative in all six columns, suggesting that the improvement in investor behaviors are more pronounced among less

sophisticated adopters. For instance, in Column (1), where the effect examined is on portfolio concentration, the significantly negative coefficient of *Post* Sophistication score* (-0.0429) indicates that less sophisticated investors improve more in terms of portfolio diversification strategy after adopting robo-advising. Overall, these findings indicate that naïve investors benefit more from learning through robo-advising.

[Insert Table 7 Here]

5.2.3 Causality of the education effect

Self-selection bias is a concern when we consider the causal effect of robo-advising on investors' behavior: there could be unobserved differences between robo-advising adopters and non-adopters, and the effects we document may be driven by such difference rather than the robo-advising's education role. A PSM sample along with individual investor fixed effects can effectively control for the unobserved time-invariant differences between adopters and non-adopters, but we still need to address the issue of unobserved time-variant factors. For instance, adopters may join another financial program that simultaneously improves their financial sophistication and persuade them to delegate investment to professional advisors. In such a scenario, the positive effect reported in section 5.2.2 could overstate the impact of robo-advising, as the behavioral changes may also be attributed to the influence of the aforementioned program.

We address this concern by exploring a BangNiTou marketing campaign. To convert more Alipay users to BangNiTou users, the firm initiated a strategy involving the random distribution of pop-up ads to Alipay users from October 2020 to December 2020. During this period, all Alipay users with account balance exceeding 100 RMB had an equal chance of receiving the ads. Targeted users would see the ads once logging into the app. Table 8 report statistics regarding the advertisement. We divide all investors having not adopted BangNiTou in our sample before October 2020 into four groups, with Group A representing investors who were exposed to the ads and adopted BangNiTou, Group B representing investors who were not exposed to the ads but adopted

BangNiTou, Group C representing investors who were exposed to the ads but did not adopt BangNiTou, and Group D representing investors who were not exposed to the ads and did not adopt BangNiTou. Of all the 150,037 investors exposed to the ads, 8.07% (12,114/150,037) adopted BangNiTou; in contrast, only 3.47% investors unexposed to the ads adopted BangNiTou, suggesting that the advertisement effectively converted more investors into robo-advising adopters. To examine the change in investor behaviors, we further require investors to have trading records in their self-directed accounts for the three months both before and after adoption. After imposing this restriction, as reported in the second row in Table 8, the percentage of BangNiTou adopters in all investors exposed to the ads is 8.87%, still higher than the percentage for investors unexposed to the ads (6.40%).[15] To check the robustness of our findings, we also construct a matching sample of non-adopters with characteristics most comparable to adopters. We conduct a 1:1 matching using the PSM method based on investor characteristics as in Table 5. Specifically, for each BangNiTou adopter, we select a non-adopter from Group C or Group D. Statistics for the PSM sample are reported in the third row of Table 8. In the matched sample, 52.13% of Alipay investors exposed to the advertisement choose to subscribe BangNiTou; in contrast, 45.82% investors unexposed to the advertisement choose to subscribe BangNiTou.

[Insert Table 8 Here]

We next use whether the Alipay investor is exposed to the ads as an instrumental variable to estimate how adopting robo-advising changes investor behaviors[16]. The advertisement is an ideal IV because: 1) investors are randomly exposed to the ads; and 2) investors receiving the ads are more likely to adopt BangNiTou. The regression model is as follows:

[15] Removing investors without trading records significantly reduces the number of investors in group D (i.e., non-adopters without exposure to BangNiTou ads), which biases the control sample. But this bias is against our finding since active traders are more likely to learn from trading. Given this bias, we still find that robo-advising significantly improves investor behaviors relative to a control group with strong self-learning ability.

[16] In the untabulated results, we also use a continuous variable, the frequency of investors' exposure to the advertisement, as the alternative IV, and obtain similar results. The frequency of exposure to BangNiTou ads can also effectively increase the probability of adopting the robo-advisor. During the period of the ads, the average ad exposure frequency is 1.369 for adopters, and 0.366 for non-adopters.

$$Chg_Bias_i = a + \beta_1 Treat_i + \gamma control_i + e_i \quad (3)$$

where Chg_Bias_i is the change in behavior bias for investor i after adoption, measured in such aspects as portfolio concentration (HHI), fund correlation, framing bias, tail return overweight, extrapolation bias, and availability bias. $Treat_i$ is set to be 1 if investor i adopts BangNiTou, and 0 otherwise. The advertisement is used as the IV of $Treat_i$ at the first stage in the 2SLS regression. Control variables are the same as in Tables 5 and 6. Tables 9 and 10 report results for the PSM sample. We also conduct the same tests using the full sample and results are similar (untabulated).

Table 9 reports results for the IV estimation. Due to the length of the paper, we only report the second stage of the 2SLS estimations to save space. Collectively, the first-stage results confirm that the exposure to BangNiTou ads is powerful in predicting investors' choices to adopt robo-advising. The coefficients for *Treat* in Columns (1) – (6) are all significantly negative, suggesting that adopting robo-advising leads to more diversified portfolios and reduced framing bias in both OLS estimations and 2SLS estimations. Table 10 reports results for investor behavioral biases in fund choice. Consistent with results reported in Tables 6, the coefficients of *Treat* in Columns (1), (3), and (5) are all significantly negative, suggesting that after adopting robo-advising, investors exhibit a reduced tail return overweight, decreased overextrapolation, and a lower degree of availability bias. Columns (2), (4) and (6) present the 2SLS results, further demonstrating that investors are less subject to tail return overweight and overextrapolation. The 2SLS result for availability bias is weaker, with the coefficient of *Treat* in Column (6) being negative but statistically insignificant. Overall, our finding that robo-advising improves investor behaviors survives the identification strategy in five out of six specifications, alleviating concerns of selection bias. In addition, the magnitude of the coefficients of *Treat* in the 2SLS regressions are generally three to four times larger

than those in the OLS regressions, suggesting that the improvement in financial behaviors is more pronounced for robo-advising adopters influenced by BangNiTou's advertising. [17]

[Insert Table 9 Here]

[Insert Table 10 Here]

6. Mechanisms of robo-advising's education effect

In this section, we propose and test two unique mechanisms that enhance the effectiveness of the robo-advisor in changing investor behavior: repeated interactions between the robo-advisor and its users, and the availability of easily applicable educational resources.

6.1 Repeated interaction intensifies the education effect

Existing literature reflects that the financial education programs examined in most prior studies are one-off interventions, which show limited effectiveness in influencing such sophisticated decisions as investment (Duflo & Saez, 2003; Lusardi & Mitchell, 2014). In contrast, the education of BangNiTou is a continuous process. BangNiTou continually updates its portfolio performance on a daily basis, motivating its adopters to log in the app regularly to monitor their portfolio performance. Once logging in the app, investors are exposed to a variety of educational materials provided by BangNiTou. Portfolio reports contain comprehensive details about the portfolios, including all the mutual funds in the portfolio and their respective performance over certain periods, and investors can track how the portfolio is rebalanced through comparing reports for different quarters. Service notes provide financial knowledge and investment skills related to portfolio management, such as how to diversify one's portfolio and avoid various behavioral biases; the app also highlights important tips and display them on its hompage page to make investors to easily access them. Each login by the adopters is an opportunity for them to access useful information from the app. These features strengthen BangNiTou's education effect through repeated interactions

[17] Another identification concern arises from investors' endogenous decisions to maintain multiple accounts, including the one delegated to BangNiTou. For instance, investors might allocate different roles to different accounts, delegating the long-term oriented investment to BangNiTou while self-managing another account for short-term purpose. Our identification of advertising campaign cannot address this within-investor endogeneity concern.

between investors and the robo-advisor. We test this by examining whether investors who interact more intensely with the robo-advisor exhibit greater improvements in their investment behaviors.

To empirically test this prediction, we utilize investors' digital footprints in the BangNiTou app and measure the intensity of the interaction between adopters and BangNiTou based on the duration of time they spend using the BangNiTou app. Investors using the app for longer durations tend to have more interactions with the robo-advisor and thus are more likely to be affected by it. Table 11 reports the results. We categorize investors into three groups based on the monthly average time investors spend using the app. *Long Duration* (*Moderate Duration*) is a dummy variable equal to 1 if the monthly average duration of time is in the top (middle) group and 0 otherwise. Variables of interest are the interaction terms of *post* and the two dummy variables, respectively, which capture the cross-sectional variation among investors with different levels of interactions.

We find that except for the extrapolation bias, the coefficients of *Post*Long Duration* are all significantly negative in other five measures of investment behaviors, indicating that investors using the BangNiTou app for a longer time have more diversified portfolios and display reduced framing bias, less tail return overweight and availability bias. Results for *Moderate Duration* are mixed, with the coefficients of *Post*Moderate Duration* being significantly negative for portfolio concentration (Column (1)), framing bias (Column (2)) and tail return overwight (Column (3)), but positive for the other three measures. Collectively, these cross-sectional analyses demonstrate that the reduction in investment behavior biases are generally more pronounced for investors who spent more time on the app, supporting our argument that robo-advising effectively improves investors' investment behaviors through repeated and continuous interactions between investors and the robo-advisor.

[Insert Table 11 Here]

We also consider two alternative proxies for the interaction intensity, namely the frequency of investor logging in the BangNiTou app and the duration of time investors spent on service notes, and

obtain similar results (untabulated), further confirming that the education effect can be reinforced by continuous interaction between the adopters and the robo-advisor.[18]

6.2 Easy-to-apply educational resources

Prior literature questioning the effectiveness of financial education in changing financial behaviors highlights that it is difficult for naïve investors to apply their acquired knowledge to financial decisions (Fernandes et al., 2014). The educational resources provided by BangNiTou may lower the difficulty of the learning and applying process. On one hand, BangNiTou's service notes provide reading materials to explain the conceptual and theoretical foundations underlying fund investment. These materials encompass multiple aspects of fund investment varying from portfolio diversification, risk-return balance, common behavioral biases, to tips to avoid potential investment pitfalls. On the other hand, BangNiTou portfolios serve as tangible examples of effective portfolio construction. By studying the portfolio reports, investors gain practical insights into fund allocation and selection. The combination of the two components mirrors the structure of most textbooks, which introduce abstract concepts first and then provide illustrative examples to help students grasp how to apply these concepts. In this manner, BangNiTou facilitates the comprehension and application of investment skills for individuals with limited financial literacy. Consequently, we propose that the combination of BangNiTou portfolios and service notes acts as a crucial mechanism to enhance the educational effect.

We test the mechanism by examining whether the educational effect is more prominent for investors who read both service notes and portfolio reports compared to those who read only one of them or none. Utilizing data on adopters' digital footprints on the BangNiTou app, we categorize adopters into four groups based on their frequency of accessing service notes and whether they have

[18] Ideally, examining how changes in certain investor behaviors are related to the content posted in service notes would provide compelling evidence of investors' learning through robo-advising. For instance, it would be interesting to investigate whether investors who read more materials on diversification are better at diversifying their portfolios thereafter. Unfortunately, conducting such tests is impractical due to data limitations; the BangNiTou App does not track specific articles that investors read in service notes.

read portfolio reports.[19] We introduce dummy variables for various groups, along with their interaction terms with *Post*, into regression model (1) for the test. Specifically, *SR* represents the group of adopters with service notes access frequency in the top 50% and having read portfolio reports, *SN* represents adopters with service notes access frequency in the top 50% but having not read portfolio reports, and *NR* represents adopters with service notes access frequency in the bottom 50% but having read portfolio reports. The baseline group consists of adopters who access service notes less frequently (in the bottom 50%) and have not read portfolio reports. The sample means for *SR*, *SN*, and *NR* are 16%, 33%, and 8%, respectively.

Table 12 reports the regression results. Except for extrapolation bias, coefficients of *SR*Post* are consistently negative and significant for the other five measures of behavioral bias, suggesting that compared to the baseline group, investors who read more service notes and simultaneously review portfolio reports experience the most substantial reduction in behavioral biases after the adoption. More importantly, the coefficients of *SR*Post* are significantly more negative than those of *SN*Post* and *NR*Post* in most columns, indicating that the improvements in investor behaviors are most pronounced for adopters who both read more services notes and review portfolio reports. These results support the notion that the combination of service notes and real-world portfolio models facilitates individuals in learning and applying investment skills, leading to more substantial changes in investor behaviors.

[*Insert Table 12 Here*]

6.3 Mimicking strategy

Investors may learn from robo-advising by simply replicating its fund portfolios in their self-directed accounts. In this section, we test this possibility by comparing the self-directed portfolios

[19] We did not partition the sample based on whether the adopter accesses the service notes as we did with portfolio reports, since the observations of adopters not accessing service notes are insufficient. Note that each time investors log in the BangNiTou app, they are automatically exposed to the service notes. Although they do not consciously read service notes, these exposures are recorded in the footprint data as accessing service notes. Therefore, it is technically infeasible to partition investors based on whether they access service notes or not.

between adopters who read portfolio reports and those who do not. If adopters mimic BangNiTou portfolios, we expect those who read portfolio reports to move their self-directed portfolios towards their BangNiTou portfolios. The mimicking behavior is depicted through five aspects: the share of the subscription to mutual funds that appear in her recent BangNiTou portfolio; the share of the subscription to mutual funds increasingly held by her recent BangNiTou portfolio; the share of the redemption of mutual funds reduced by her recent BangNiTou portfolio; the share of the subscription to mutual funds managed by fund companies that appear in her BangNiTou portfolio; and a similarity in investment style index between the investor's self-directed portfolio and BangNiTou portfolio, constructed based on measures including a market factor, size factor, valuation factor, momentum factor, and exposure to industry.

Table 13 presents the results. Investors who read portfolio reports purchase more mutual funds that are present in their recent BangNiTou portfolios, purchase more funds that are increasingly held in their BangNiTou portfolios and managed by fund companies featured in their BangNiTou portfolios, divest funds that BangNiTou holds less of, and have an investment style index more similar to BangNiTou. These findings collectively suggest that investors learn from robo-advising by holding self-directed portfolios more similar with their BangNiTou portfolios. For instance, in the first quarter after adopting BangNiTou, on average, the share of the subscription to mutual funds that are present in their recent BangNiTou portfolios for investors who have read BangNiTou reports is 1.11%, significantly higher than that for investors who have not read reports (0.92%). Similar patterns are observed in the second and third quarters. However, the economic magnitude of the difference between the two statistics (1.11% and 0.92%) is relatively small, implying that on average, adopters do not entirely replicate BangNiTou's advised portfolios. Similar patterns are observed for the other behaviors reported in Table 13. Taken together, our findings imply that replicating BangNiTou's portfolios should not be a prominent method through which adopters learn from the robo-advisor.

[Insert Table 13 Here]

7. The impact of robo-advising on adopters' self-directed investment performance

Given that robo-advising improves adopters' investment behaviors, we expect that they achieve better investment performance in their self-directed portfolios after the adoption. In this section, we investigate this possibility using the following two regression models:

$$DepVar_{i,period} = a + \beta post_i + v_i + e_{i,period}. \quad (4)$$

$$DepVar_{i,period} = a + \beta_1 post_i + \beta_2 Treat_i \times post_i + v_i + e_{i,period} \quad (5)$$

The dependent variables are measures of portfolio performance including style-adjusted abnormal Sharpe ratio, style-adjusted abnormal volatility and style-adjusted abnormal return. *Post* is defined as 1 for observations after the adoption, and 0 otherwise. *Treat* is defined as 1 for investors who adopt robo-advising, and 0 otherwise. Model (4) examines the change in adopters' self-directed portfolio performance after they interact with the robo-advisor. Only robo-advising adopters are included in Model (4), and the variable of interest is *Post*, which captures the change in adopters' self-directed portfolio performance after the adoption. Model (5), a DID specification, is used to examine the change in performance of adopters' self-directed portfolios relative to non-adopters' portfolios. The treat and control group are the same as in Model (2). In Model (5), the variable of interest is the interaction term $Treat_i \times post_i$, which captures the additional effect of robo-advising on investment performance of adopters relative to non-adopters. Individual investor fixed effects are included to control for time-invariant unobserved individual investor heterogeneity. The sample for these tests is the same as in Table 5 and 6.

[Insert Table 14 Here]

Results are reported in Table 14. The coefficients of *Post* are all significantly positive in column (1), (3), and (5), suggesting that robo-advising adopters' self-directed portfolios exhibit higher style-adjusted return, higher style-adjusted volatility and higher style-adjusted Sharpe ratio after the adoption. Coefficients of the interaction term $Treat_i \times post_i$ in column (2), (4) and (6) are all

significantly positive, indicating that the increase in style-adjusted return, style-adjusted volatility, and style-adjusted Sharpe ratio of robo-advising adopters' self-directed portfolios after the adoption is even larger than that of non-adopters' portfolios. Despite the higher portfolio volatility, both the portfolio Sharpe ratio and return increase significantly, suggesting that overall, investors' self-directed portfolios achieve better performance after adopting robo-advising services. These findings are consistent with the argument that investors learn from robo-advising and become more financially sophisticated in mutual fund investment.

As to the economic magnitude of the improvement of Sharpe ratio, the coefficient of $Treat_i \times post_i$ is 0.0033, equivalent to approximately 6.7% of the average style-adjusted Sharpe ratio before adopting robo-advising (-0.049). In contrast, as shown in Table 3, the average style-adjusted Sharpe ratio for robo-advising portfolio is 0.041, indicating a significant improvement in investor performance by 0.090 (0.041 + 0.049). Comparing with the direct effect of adopting robo-advising, i.e., the enhanced performance of robo-advising portfolios, the financial education effect of robo-advising leads to a relatively modest performance improvement. This comparison implies that it is better for small and less sophisticated investors to delegate their investments to robo-advisory than to self-manage them (keeping in mind that the superior performance of the BangNiTou portfolio is after accounting for management fees).

8. Conclusion

Utilizing an individual-investor-account level dataset provided by BangNiTou and Alipay, this study empirically examines the spillover effect of robo-advising, particularly its financial education impact on investors that adopt it. We find that after the adoption, investors' self-directed accounts display reduced behavioral biases in portfolio management and fund choices, indicating that robo-advising effectively improves investor behaviors.

This study has important policy implications. While financial education literature underscores the importance of equipping individuals with adequate financial knowledge for participation in risky

asset investment, traditional financial education programs are often expensive and inaccessible, particularly for low-income and young households. The rise of robo-advising provides a practical solution. By leveraging information technology and algorithms, robo-advisors can efficiently manage numerous small accounts at a significantly low cost, making advisory services more accessible to the average investor. For example, now BangNiTou's minimum account requirement is only 100 RMB, or less than 15 USD. By integrating educational resources in its smartphone app, where investors can access these materials with just a few clicks at their convenience, BangNiTou substantially reduce the cost of education for most investors.

The effectiveness of Robo-advising as a financial education tool for risky investment participation is closely tied to its various features. It primarily affects individuals who are seeking to acquire relevant skills to enhance their investment performance and thus having strong motivation to learn. For these individuals, the perceived relevance is also high, meaning that it is easy for them to relate what they learn from robo-advising with their own investment decisions. In addition, its effect can be amplified when the learning materials are well-designed for education purposes, such as incorporating mechanisms to increase the frequency of accessing the educational content and reduce the difficulty for investors to transfer knowledge into changes in investment behaviors. We call for more studies to identify how to design and incorporate education content in robo-advising to further enhance its education effect.

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Appendix: Variable Definitions

A. Demographics and portfolio characteristics

Female: a dummy variable that equals 1 if the investor is a woman, and 0 otherwise.
Age: the age of an investor
Top city: a dummy variable that equals 1 if the investor resides in the largest 18 cities in China, and 0 otherwise. The 18 cities are Beijing, Shanghai, Guangzhou, Shenzhen, Wuhan, Nanjing, Chengdu, Chongqing, Hangzhou, Tianjin, Suzhou, Changsha, Qingdao, Xi'an, Zhengzhou, Ningbo, Wuxi, and Dalian.
Total Assets: the amount of total assets in Alipay account at the end of month *t*.
YuErBao Ratio: the *YuErBao* amount held by investor *i* at the end of month *t* divided by total assets. *YuErBao* is the largest money market fund in China operated by Alipay's subsidiaries.
WMPs Ratio: the amount of wealth management products (WMPs) held by investor *i* at the end of month *t* divided by total assets. WMP is an off-balance-sheet substitute for deposits that is widespread in China with investment return and risk slightly higher than deposits but much lower than mutual funds.
Mutual Fund Ratio: the amount of mutual funds held by investor *i* at the end of month *t* divided by total assets.
Fund Num: the number of funds held by investor *i* at the end of month *t*.
Mutual Fund: the amount of mutual funds held by investor *i* at the end of month *t*.
Debt Fund Ratio: the amount of debt funds held by investor *i* at the end of month *t* divided by the amount of mutual funds.
Debt Fund Ratio: the amount of debt funds held by investor *i* at the end of month *t* divided by the amount of mutual funds.
Equity Fund Ratio: the amount of equity funds held by investor *i* at the end of month *t* divided by the amount of mutual funds.
Index Fund Ratio: the amount of index funds held by investor *i* at the end of month *t* divided by the amount of mutual funds.
Fund Subscription: the amount of funds subscribed by investor *i* in month *t*.
Fund Redemption: the amount of funds redeemed by investor *i* in month *t*.
Transaction Num: the total number of subscriptions and redemptions by investor *i* in month *t*.
Portfolio Turnover: the total amount of fund subscriptions and redemptions by investor *i* in month *t* divided by the average amount of mutual funds at the beginning and end of month *t*.

B. Usage of Robo-advisors

BangNiTou Asset: the amount of assets delegated to BangNiTou by investor *i* at the end of month *t*.
BangNiTou Ratio: the amount of assets delegated to BangNiTou by investor *i* at the end of month *t* divided by total assets.
BangNiTou Subscription: the amount of assets delegated to BangNiTou subscribed by investor *i* in month *t*.
BangNiTou Redemption: the amount of assets delegated to BangNiTou redeemed by investor *i* in month *t*.
BangNiTou Turnover: the total amount of BangNiTou subscriptions and redemptions by investor *i* in month *t* divided by the average amount of BangNiTou assets at the beginning and end of month *t*.
BangNiTou Logins: the number of times that investor *i* logs in to the BangNiTou App in month *t*.
BangNiTou Stay: the length of time that investor *i* spends on the BangNiTou app in month *t*.

C. Portfolio Performance

Style-adjusted Sharpe ratio: the difference between a portfolio's Sharpe ratio and its benchmark portfolio's Sharpe ratio. Sharpe ratio is defined as the ratio of the daily average portfolio return over the standard deviation of daily portfolio return in month *t*. The return of portfolio *i* in day *d* ($r_{i.d}$) is defined as follows:

$$r_{i,d} = \sum_{j=1}^{n} \frac{m_{i,j,d-1}}{\sum_{j=1}^{n} m_{i,j,d-1}} \times r_{j,d}$$

$$r_{j,d} = \ln\left(\frac{AdjNAV_{j,d}}{AdjNAV_{j,d-1}}\right)$$

where $m_{i,j,d-1}$ is the market value of fund *j* in portfolio *i* on day *d-1* and $AdjNAV_{j,d}$ ($AdjNAV_{j,d-1}$) is the net asset value of fund *j* on day *d* (*d-1*) after adjusting for splits or dividends. The benchmark portfolio of any portfolio *i* is constructed with the same share of equity and debt funds as portfolio *i* and using marketwide average performance for equity funds and debt funds to replace portfolio *i*'s actual performance.

Style-adjusted return: the difference between a portfolio's monthly return and its benchmark portfolio's monthly return. Portfolio monthly return is defined as the accumulated daily portfolio return in a given month. The benchmark portfolio and its performance are constructed in the same way as the style-adjusted Sharpe ratio.

Style-adjusted volatility: the difference between a portfolio's volatility and its benchmark portfolio's volatility. Portfolio volatility is defined as the standard deviation of daily portfolio return in a given month. The benchmark portfolio and its performance are constructed in the same way as the style-adjusted Sharpe ratio.

D. Investment Behaviors

Portfolio concentration: the Herfindal index (HHI) of the portfolio is $\sum_{i=1}^{N} \lambda_i^2$, where λ_i equals the ratio between the value of mutual fund *i* and the total value of the fund portfolio at the end of a given month. The higher the HHI measure, the more concentrated a portfolio is.

Fund Correlation: the average correlation among funds in a portfolio. We first calculate the Spearman correlation between each fund and the whole portfolio using daily returns in a given month and then use the weighted-average correlation for all funds in the portfolio as the *Fund Correlation* measure. The higher the correlation measure, the less the portfolio is diversified.

Framing bias: following Bailey et al (2011), we measure the monthly framing bias as 1 minus the ratio of trading frequency to the number of days with trading for investor *i* in a given month. The higher the measure, the more likely investors trade a single asset in a given day and the higher the framing bias.

Availability bias: the percentage of investor *i*'s subscription to attention-grabbing funds among all his/her subscriptions in month *t*. A higher percentage indicates a larger probability that the investor is subject to availability bias. We define a fund to be attention-grabbing if it is ranked in the top 10% of performance over the last month or the top 10% of subscriptions over the last month.

Extrapolation bias: the percentage of investor *i*'s subscriptions for momentum funds among all his/her subscriptions in month *t*. A higher percentage indicates a larger probability that the investor is subject to the extrapolation bias. Momentum funds is defined as those whose performance is ranked in the top 20% of mutual funds of the same style over the past 12 months.

Tail return overweight: the value-weighted average lottery score of all funds in a portfolio. The higher the measure, the stronger the tendency to overweight tail returns. Following Han and Kumar (2013), the lottery score of a fund in a given month is defined as the sum of the vigintile assignments to its idiosyncratic volatility, idiosyncratic skewness, and net asset value divided by 60. Net asset value is the average daily net asset value of the fund in that month. Idiosyncratic volatility is the volatility of the residual obtained from regressing the fund's daily returns on market returns. Idiosyncratic skewness is the third moment of the residual obtained by fitting a two-factor model (market returns and the square of market returns). Idiosyncratic volatility and idiosyncratic skewness are both estimated using daily returns over the past six months.

Table 1 Descriptive statistics of BangNiTou adopters (before the adoption)

Table 1 presents descriptive statistics of demographic characteristics, portfolio holdings, and trading behaviors of BangNiTou adopters during the twelve months before adoption. Regarding portfolio characteristics and trading behaviors, we first calculate the average of each variable for each investor across the twelve months before adoption and report descriptive statistics for the averaged numbers. Descriptive statistics include the sample mean (Mean), the sample standard deviation (SD), the sample maximum (Max) and minimum (Min) values, the sample 25^{th} (P25) and 75^{th} (P75) quantiles, and the sample median (Median). The number of BangNiTou adopters in our final sample is 74,090.

Variables	Mean	SD	Min	P25	Median	P75	Max
Female	0.296	0.456	0	0	0	1	1
Age	30.844	7.946	20	25	29	34	60
Top city	0.587	0.492	0	0	1	1	1
Total Assets	67665	119081	296	6781	24272	74089	647799
YuErBao Ratio	0.314	0.252	0.001	0.103	0.246	0.478	0.943
WMPs Ratio	0.270	0.297	0.000	0.006	0.142	0.487	0.943
Mutual Fund Ratio	0.397	0.280	0.003	0.144	0.371	0.620	0.976
Fund Num	6.783	8.876	1.000	2.000	3.889	7.917	71.000
Mutual Fund	23327	55122	14	1000	4975	19878	477642
Debt Fund Ratio	0.265	0.298	0.000	0.007	0.144	0.450	1.000
Equity Fund Ratio	0.704	0.304	0.000	0.500	0.812	0.971	1.000
Index Fund Ratio	0.288	0.277	0.000	0.046	0.212	0.458	1.000
Fund Subscription	8330	18345	10	488	2020	7398	137558
Fund Redemption	6595	15998	0	201	1258	5278	128984
Transaction Num	7.578	13.411	0.286	1.750	3.400	7.182	111.042
Portfolio Turnover	1.298	1.440	0.026	0.388	0.824	1.624	7.953

Table 2 Descriptive statistics of BangNiTou adopters (after the adoption)

Table 2 presents descriptive statistics of portfolio characteristics, trading behaviors, and digital footprints of BangNiTou adopters during the eight months after the adoption. We calculate the average of each variable for each investor over the eight months post adoption and report descriptive statistics for the averaged numbers. The descriptive statistics include the sample mean (Mean), the sample standard deviation (SD), the sample maximum (Max) and minimum (Min) values, the sample 25^{th} (P25) and 75^{th} (P75) quantiles, and the sample median (Median). The number of BangNiTou adopters in our final sample is 74,090.

Variables	Mean	SD	Min	P25	Median	P75	Max
Total Assets	113087	167213	296	16457	49561	131342	890045
YuErBao Ratio	0.230	0.212	0.001	0.068	0.163	0.333	0.943
WMPs Ratio	0.205	0.258	0.000	0.000	0.074	0.354	0.943
Mutual Fund Ratio	0.470	0.275	0.003	0.233	0.467	0.699	0.976
Fund Num	12.458	13.279	1.000	4.000	8.125	15.500	71.000
Mutual Fund	50736	87685	14	5014	17379	53146	477642
Debt Fund Ratio	0.151	0.231	0.000	0.000	0.036	0.208	1.000
Equity Fund Ratio	0.800	0.247	0.000	0.702	0.900	0.991	1.000
Index Fund Ratio	0.261	0.236	0.000	0.064	0.208	0.394	1.000
Fund Subscription	12368	23287	10	1020	3820	12092	137558
Fund Redemption	11223	22086	0	627	3022	10578	128984
Transaction Num	12.652	19.869	0.286	2.500	5.200	13.250	111.042
Portfolio Turnover	0.902	1.178	0.026	0.248	0.521	1.067	7.953
BangNiTou Asset	4584	10074	0	225	1026	3844	66074
BangNiTou Ratio	0.065	0.100	0.000	0.004	0.024	0.079	0.534
BangNiTou Subscription	2116	5146	0	54	335	1542	35000
BangNiTou Redemption	855	2398	0	9	83	490	16675
BangNiTou Turnover	1.254	2.304	0.000	0.096	0.447	1.298	14.950
BangNiTou Logins (1st Month)	43	76.603	0	7	20	49	2363
BangNiTou Stay (1st Month)	421	638	0	80	221	507	24526
BangNiTou Logins	17	24	0	2	7	20	122
BangNiTou Stay	161	228	0	23	72	196	1139

Table 3 Investment performance: self-directed portfolios vs. BangNiTou portfolios

Table 3 compares the style-adjusted investment performance for BangNiTou portfolios and investors' self-directed portfolios during the windows of [–12, –1] and [1, 8], with 0 representing the month of adopting the robo-advisor. We measure performance from three dimensions: the Sharpe ratio, portfolio return, and volatility. The Sharpe ratio is defined as the ratio of the daily average portfolio return over the standard deviation of daily portfolio return in a given month. Portfolio monthly return is defined as the accumulated daily portfolio return in a given month. Portfolio volatility is defined as the standard deviation of daily portfolio return in a given month. Style-adjusted performance measure is defined as the difference between a portfolio' own performance and its benchmark portfolio's performance. See Appendix A for detailed definitions of variables. The column headed with "(3)–(1)" ("(3)–(2)") display the performance difference between BangNiTou portfolios and investors' self-directed portfolios before (after) adoption. The sample mean (Mean) and its standard errors (SE) in each group are reported, and the values in bold are significant at the 1% significance level.

		Self-Directed Portfolios		BangNiTou Portfolios		
		[–12, –1]	[1, 8]	[1, 8]		
Variables		(1)	(2)	(3)	(3)–(1)	(3)–(2)
Style-adjusted Sharpe Ratio	Mean	**-0.049**	**-0.012**	**0.041**	**0.090**	**0.052**
	SE	0.0005	0.0003	0.0008	0.0010	0.0009
Style-adjusted Monthly return	Mean	**-0.003**	**0.006**	**0.001**	**0.004**	**-0.005**
	SE	0.0001	0.0002	0.0000	0.0001	0.0002
Style-adjusted Volatility	Mean	**0.004**	**0.010**	**0.003**	**-0.001**	**-0.007**
	SE	0.0000	0.0001	0.0000	0.0000	0.0001

Table 4 Analysis of what investor characteristics determine the adoption

Table 4 presents results for the Probit model regression of what investor characteristics determine the robo-advising adoption. The dependent variable is whether the investor signs up for BangNiTou, and independent variables include average portfolio characteristics and investment behaviors over the 12 months before the adoption. Column (1) presents the results using the full sample comprising of all adopters and non-adopters obtained through the stratified sampling. Column (2) displays the results using the sample of robo-advising adopters and matched non-adopters. Coefficients and their robust standard errors are reported. Here, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables：Adopt Robo-Advising (1/0)		
	(1)	(2)
	Pre-Match	Post-Match
Log (Total assets)	-0.0510***	0.0017
	(0.001)	(0.002)
Style-adjusted return	2.6745***	-0.2614
	(0.114)	(0.195)
Style-adjusted volatility	-15.3650***	-0.3413
	(0.539)	(0.897)
Style-adjusted Sharpe ratio	0.0792***	0.0372
	(0.017)	(0.027)
WMPs ratio	0.3951***	0.0209
	(0.010)	(0.016)
Debt fund ratio	-0.3717***	-0.0444
	(0.020)	(0.033)
Equity fund ratio	-0.4550***	0.0513**
	(0.012)	(0.021)
Index fund ratio	0.0479***	-0.0287
	(0.015)	(0.028)
Portfolio concentration	-0.2617***	0.0062
	(0.011)	(0.018)
Fund correlation	-0.2753***	-0.0034
	(0.013)	(0.021)
Framing bias	-0.0502***	-0.0031
	(0.002)	(0.004)
Tail return overweight	0.0169***	0.0061
	(0.003)	(0.005)
Extrapolation bias	-0.1852***	0.0028
	(0.008)	(0.013)
Availability bias	-0.4987***	-0.0171
	(0.018)	(0.030)
Portfolio turnover	0.0189***	0.0029
	(0.002)	(0.003)
Log (Transaction Num)	-0.0020***	-0.0002

	(0.000)	(0.000)
Constant	-0.2393***	-0.0348
	(0.018)	(0.030)
Obs.	879132	148180
Pseudo R^2	0.0452	0.0001

Table 5 Impact of robo-advising on behavioral biases in portfolio management

Table 5 presents how robo-advising impacts adopters' self-directed portfolio management. We analyze the effect using two models. In Model (1), the sample only includes adopters and the regression equation is as follows:

$$DepVar_{i,period} = a + \beta post_i + \gamma control_{i,period} + v_i + e_{i,period.} \quad (1)$$

The dependent variables include *portfolio concentration*, *fund correlation*, and *framing bias*. Subscript *i* denotes investor *i*. Subscript *period* equals 1 for observations after the adoption, and 0 otherwise. *Post* equals 1 for observations following the adoption, and 0 otherwise. All monthly observations are averaged into investor-period level for the analysis. In Model (2), we estimate the effect using the sample including both adopters and matched non-adopters constructed in Section 4 and the regression equation is as follows:

$$DepVar_{i,period} = a + \beta_1 post_i + \beta_2 Treat_i \times post_i + \gamma control_{i,period} + v_i + e_{i,period.} \quad (2)$$

Treat equals 1 for investors who adopt robo-advising, and 0 otherwise. Other variables are the same as in Model (1). Individual investor fixed effects are included in all specifications. The regression coefficients and robust standard errors are reported. Standard errors are clustered by investors. Here, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Portfolio concentration		*Fund correlation*		*Framing bias*	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Post	-0.0825***	-0.0344***	-0.0608***	-0.0244***	-0.2918***	-0.0934***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.006)
*Treat*Post*		-0.0506***		-0.0367***		-0.2004***
		(0.001)		(0.001)		(0.008)
Log (Total assets)	-0.0686***	-0.0645***	-0.0234***	-0.0231***	-0.1059***	-0.095***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.004)
Style-adjusted Sharpe ratio	0.1043***	0.0973***	0.1573***	0.1502***	0.0336	0.015
	(0.006)	(0.005)	(0.006)	(0.005)	(0.031)	(0.023)
Equity fund ratio	-0.2***	-0.191***	0.0772***	0.0777***	-0.5011***	-0.2971***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.023)	(0.016)
Portfolio concentration					1.4668***	1.5026***
					(0.023)	(0.017)
Framing bias	0.0374***	0.0449***	0.0066***	0.008***		
	(0.001)	(0.001)	(0.001)	(0.000)		

Tail return overweight	0.0054***	0.0036***	-0.0455***	-0.0441***	-0.0412***	-0.0246***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.004)
Extrapolation bias	-0.0295***	-0.0285***	0.0337***	0.032***	0.1099***	0.0732***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.013)	(0.009)
Availability bias	-0.0804***	-0.0919***	0.0086	-0.008	-0.1157***	-0.1002***
	(0.007)	(0.005)	(0.006)	(0.004)	(0.032)	(0.022)
Portfolio turnover	0.011***	0.0113***	-0.0121***	-0.0127***	-0.0851***	-0.0766***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Constant	1.3029***	1.2715***	0.8789***	0.885***	-0.4264***	-0.5959***
	(0.010)	(0.008)	(0.009)	(0.007)	(0.065)	(0.048)
Investor FE	Y	Y	Y	Y	Y	Y
Obs.	148180	286272	148180	286272	148180	286272
Adjusted R^2	0.485	0.4182	0.1338	0.12	0.2312	0.2015

Table 6 Impact of robo-advising on behavioral biases in fund choices

Table 6 analyzes how robo-advising impacts adopters' behavioral biases in fund choices. We analyze the effect using two models. In Model (1), the sample only includes investors who adopt robo-advising, and the regression equation is as follows:

$$DepVar_{i,period} = a + \beta post_i + \gamma control_{i,period} + v_i + e_{i,period}. \quad (1)$$

The dependent variables include *availability bias*, *extrapolation bias*, and *tail return overweight*. Subscript *i* denotes investor *i*. Subscript *period* equals 1 for observations post adoption, and 0 otherwise. *Post* equals 1 for observations following the adoption, and 0 otherwise. All monthly observations are averaged into investor-period level for the analysis. In Model (2), we estimate the effect using the sample including both adopters and matched non-adopters constructed in Section 4, and the regression equation is as follows:

$$DepVar_{i,period} = a + \beta_1 post_i + \beta_2 Treat_i \times post_i + \gamma control_{i,period} + v_i + e_{i,period}. \quad (2)$$

Treat equals 1 for investors who adopt robo-advising, and 0 otherwise. Other variables are defined the same as in Model (1). Individual investor fixed effects are included in all specifications. The regression coefficients and robust standard errors are reported. Standard errors are clustered by investors. Here, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Tail return overweight		*Extrapolation bias*		*Availability bias*	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Post	0.0351***	0.0443***	0.1534***	0.1556***	-0.0086***	-0.0046***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
*Treat*Post*		-0.0069***		-0.0077***		-0.0069***
		(0.001)		0.0024		0.0009
Log (Total assets)	0.0027***	0.0016***	0.001	0.0011	0.0057***	0.0052***
	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
Style-adjusted Sharpe ratio	-0.0465***	-0.0496***	-0.078***	-0.0657***	0.0403***	0.0488***
	(0.003)	(0.003)	(0.010)	(0.008)	(0.004)	(0.003)
Equity fund ratio	0.1279***	0.12***	0.1955***	0.1778***	0.0716***	0.0624***
	(0.002)	(0.001)	(0.006)	(0.005)	(0.003)	(0.002)
Portfolio concentration	-0.0027	-0.0008	-0.1021***	-0.1093***	-0.0427***	-0.0525***
	(0.002)	(0.002)	(0.006)	(0.006)	(0.003)	(0.002)
Framing bias	-0.0011***	-0.0011***	0.0082***	0.0068***	-0.0006	-0.0009***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)

Portfolio turnover	0.0052***	0.0048***	0.0142***	0.0171***	0.0167***	0.0175***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	0.4635***	0.4805***	0.4495***	0.4598***	0.0652***	0.0792***
	(0.005)	(0.004)	(0.018)	(0.015)	(0.008)	(0.007)
Investor FE	Y	Y	Y	Y	Y	Y
Obs.	148180	286272	148180	286272	148180	286272
Adjusted R^2	0.2311	0.2398	0.2091	0.1911	0.0448	0.0431

Table 7 Adopters' sophistication and the education effect

Table 7 investigates whether the spillover effect of robo-advising varies with adopters' financial sophistication. The dependent variables are *portfolio concentration*, *fund correlation*, *framing bias*, *availability bias*, *extrapolation bias*, and *tail return overweight*. Following Calvet, Campbell, and Sodini (2009), we construct investors' *Sophistication score* based on their behavioral biases in self-directed investment accounts before adopting robo-advising. The higher investors' *Sophistication score*, the more behavioral biases they exhibit in portfolio management and fund selection, and the less sophisticated they are. The interaction term, *Post* Sophistication score*, is used to capture the variation in the spillover effect related to investor financial sophistication. The regression coefficients and robust standard errors are reported. Standard errors are clustered by investors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Portfolio concentration	*Fund correlation*	*Framing bias*	*Tail return overweight*	*Extrapolation bias*	*Availability bias*
Post* Sophistication score	**-0.0429*****	**-0.0415*****	**-0.0287*****	**-0.0215*****	**-0.1246*****	**-0.0576*****
	(0.002)	**(0.001)**	**(0.008)**	**(0.001)**	**(0.006)**	**(0.001)**
Post	0.0061***	0.0514***	-0.3344***	0.062***	0.3457***	0.0705***
	(0.001)	(0.001)	(0.010)	(0.001)	(0.002)	(0.001)
Constant	1.1263***	0.7716***	-0.4308***	0.4563***	0.3639***	0.0498***
	(0.009)	(0.008)	(0.065)	(0.005)	(0.015)	(0.007)
Control Variables	Y	Y	Y	Y	Y	Y
Investor FE	Y	Y	Y	Y	Y	Y
Obs.	148180	148180	148180	148180	148180	148180
Adjusted R^2	0.5984	0.3274	0.2322	0.2777	0.4181	0.2844

Table 8 Statistics on the subsample for identification

Table 8 presents statistics for the sample of identification. Group A comprises investors who have been exposed to the ads and adopt BangNiTou, Group B comprises investors who have not been exposed to the ads but adopt BangNiTou, Group C comprises investors who have been exposed to the ads but do not adopt BangNiTou, and Group D comprises investors who have not been exposed to the ads and do not adopt BangNitou. The last two columns on the right present the percentage of BangNiTou adopters among investors exposed and unexposed to the robo-advisor advertisement, respectively.

Sample selection	Group				Percent of BNT adopter	
	A	B	C	D	Exposed to the advertisement	
					Yes	No
All investors from Alipay during the sample period	12,114	5,930	137,923	164,759	8.07%	3.47%
Investors with trading records both before and after adoption	9,038	4,017	92,882	58,744	8.87%	6.40%
PSM sample	8,792	3,943	8,072	4,663	52.13%	45.82%

Table 9 The IV estimation results for portfolio management

Table 9 reports the IV estimation results regarding portfolio management. The regression model is as follows:

$$Chg_Bias_i = a + \beta_1 Treat_i + \gamma control_i + e_i. \quad (3)$$

The dependent variable is the change in investor *i*'s average investment characteristics after the robo-advising adoption. The dimensions examined include *portfolio concentration*, *fund correlation*, and *framing bias*. *Treat* equals 1 for investors who adopt robo-advising, and 0 otherwise. The instrumental variable is a dummy variable that equals 1 if the investor is exposed to the BNT advertisement when he/she logs in to the wealth front page of Alipay, and 0 otherwise. Control variables are investors' investment characteristics before adoption. The regression coefficients and robust standard errors are reported. There are 25,470 individual observations in the subsample for identification. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Portfolio concentration		*Fund correlation*		*Framing bias*	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	**-0.0945*** **	**-0.4146*** **	**-0.0509*** **	**-0.1367*** **	**-0.4116*** **	**-2.0888*** **
	(0.003)	**(0.060)**	**(0.002)**	**(0.041)**	**(0.017)**	**(0.335)**
Log (Total assets)	-0.0113***	-0.0110***	-0.0033***	-0.0033***	-0.008	-0.009
	(0.009)	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)
Style-adjusted Sharpe ratio	0.1562***	0.1546***	0.2244***	0.2243***	-0.122	0.1153
	(0.013)	(0.015)	(0.012)	(0. 012)	(0.066)	(0.078)
Equity fund ratio	-0.1291***	-0.1343***	0.0325***	0.0327***	-0.1947***	0.2248***
	(0.007)	(0.008)	(0.005)	(0.005)	(0.042)	(0.050)
Portfolio concentration					-0.0948***	0.0883
					(0.039)	(0.050)
Framing bias	0.0308***	0.0308***	-0.0081***	-0.0081***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Tail return overweight	0.0095***	0.013***	-0.0565***	-0.0566***	0.0504***	0.0689***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.012)	(0.015)
Extrapolation bias	-0.0256***	-0.0168**	0.0092	-0.0089	-0.1155***	0.069
	(0.006)	(0.007)	(0.005)	(0.005)	(0.031)	(0.038)
Availability bias	-0.0507***	-0.0424**	0.119***	-0.1187***	-0.1403**	-0.0976

	(0.015)	(0.017)	(0.012)	(0.012)	(0.072)	(0.087)
Portfolio turnover	0.0045***	0.005***	-0.0078***	-0.0078***	-0.0198***	-0.0224***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.007)	(0.008)
Constant	-0.0874***	-0.2795***	0.0938***	0.0881***	-0.1602***	-0.6554***
	(0.002)	(0.011)	(0.009)	(0.022)	(0.071)	(0.184)

Table 10 The IV results of the spillover effect on investors' behavioral biases in self-directed fund choices

Table 10 estimates the impact of robo-advising on adopters' behavioral biases in self-directed fund choices using the instrumental variable approach. The regression equation is as follows:

$$Chg_Bias_i = a + \beta_1 Treat_i + \gamma control_i + e_i. \quad (3)$$

The dependent variable is the change of investor *i*'s average behavioral biases after signing up for robo-advising. The dimensions include *availability bias*, *extrapolation bias*, and *tail return overweight*. *Treat* equals 1 for investors who adopt robo-advising, and 0 otherwise. The instrumental variable is a dummy variable that equals 1 if the investor is exposed to a BNT advertisement when he/she logs in to the wealth front page of Alipay, and 0 otherwise. Control variables are investors' average investment characteristics before signing up for robo-advising. The regression coefficients and robust standard errors are reported. There are 25,470 individual observations in the subsample for identification. Here, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Tail return overweight		*Extrapolation bias*		*Availability bias*	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	**-0.0055*** **	**-0.0171*** **	**-0.0087***	**-0.0194** **	**-0.0072*** **	**-0.0286**
	(0.001)	**(0.056)**	**(0.005)**	**(0.087)**	**(0.002)**	**(0.033)**
Log (Total assets)	-0.0049	-0.0048	-0.0122***	-0.0122***	-0.0029***	-0.0029***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Style-adjusted Sharpe ratio	-0.9155***	-0.9184***	-0.0525***	-0.0521***	-0.0391***	-0.0398***
	(0.051)	(0.052)	(0.020)	(0.020)	(0.008)	(0.008)
Equity fund ratio	1.5166***	1.5147***	-0.2176***	-0.2178***	-0.0516***	-0.0521***
	(0.019)	(0.019)	(0.010)	(0.010)	(0.004)	(0.004)
Portfolio concentration	0.0484	0.0477	0.0966***	0.0965***	0.0491***	0.0489***
	(0.026)	(0.026)	(0.012)	(0.012)	(0.005)	(0.005)
Framing bias	0.0232***	0.0233***	0.0024	0.0024	0.0001	0.0001
	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
Portfolio turnover	0.0298***	0.0295***	-0.0215***	-0.0216***	-0.0148***	-0.0149***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0. 6990***	0.8084***	0.3370***	0.3222***	0.0569***	0.0295
	(0.042)	(0.095)	(0.020)	(0.044)	(0.009)	(0.019)

Table 11 Interaction intensity and the education effect

Table 11 explores how the intensity of investors' interaction with robo-advising influences the education effect. In this table, the interaction intensity is proxied by the monthly average duration of time the investor spends using the BangNiTou app. We divide all BangNiTou adopters into three subgroups on the basis of the duration, and define adopters in the top (middle) group as *Long Duration* (*Moderate Duration*) to be 1 and 0 otherwise. Variables of interest are the two interaction items, *Post*Long Duration* and *Post*Moderate Duration*. The dependent variables are *portfolio concentration*, *fund correlation*, *framing bias*, *availability bias*, *extrapolation bias*, and *tail return overweight*. Regression coefficients and standard errors clustered by investors are reported. Here, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Portfolio concentration	*Fund correlation*	*Framing bias*	*Tail return overweight*	*Extrapolation bias*	*Availability bias*
Post*Long Stay	**-0.0045*****	**-0.0029****	**-0.1636*****	**-0.0263*****	**0.0036**	**-0.0022****
	(0.002)	**(0.001)**	**(0.012)**	**(0.007)**	**(0.003)**	**(0.001)**
Post*Moderate Stay	**-0.0032****	**0.0042*****	**-0.2511*****	**-0.0165*****	**0.0012**	**0.0012**
	(0.002)	**(0.002)**	**(0.012)**	**(0.007)**	**(0.003)**	**(0.001)**
Post	-0.0827***	-0.0616***	-0.2298***	-0.3691***	0.1525***	-0.0083***
	(0.001)	(0.001)	(0.010)	(0.006)	(0.002)	(0.001)
Constant	1.3224***	0.8837***	-0.3819***	-0.2172***	0.448***	0.0644***
	(0.010)	(0.009)	(0.074)	(0.043)	(0.018)	(0.008)
Control Variables	Y	Y	Y	Y	Y	Y
Investor FE	Y	Y	Y	Y	Y	Y
Obs.	148180	148180	148180	148180	148180	148180
Adjusted R^2	0.4812	0.1333	0.214	0.1775	0.2092	0.0452

Table 12 The interplay of BangNiTou portfolios and service notes

Table 12 reports results on the interplay of BangNiTou portfolios and service notes. We categorize adopters into four groups based on their frequency of accessing service notes and whether they read portfolio reports. *SR* denotes adopters with service notes access frequency in the top 50% and having read portfolio reports, *SN* represents adopters with service notes access frequency in the top 50% but having not read portfolio reports, and *NR* comprises adopters with service notes access frequency in the bottom 50% but having read portfolio reports. The dependent variables are *portfolio concentration*, *fund correlation*, *framing bias*, *availability bias*, *extrapolation bias*, and *tail return overweight*. The regression coefficients and standard errors clustered by investors are reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Portfolio concentration	*Fund correlation*	*Framing bias*	*Tail return overweight*	*Extrapolation bias*	*Availability bias*
SR*Post	**-0.0102*** **	**-0.0111*** **	**-0.3971*** **	**-0.0027** **	**0.0055**	**-0.0056*** **
	(0.0027)	**(0.0024)**	**(0.0345)**	**(0.0013)**	**(0.0045)**	**(0.0013)**
*SN*Post*	-0.0085***	-0.0038	-0.2182***	0.0046***	0.0061	0.0035**
	(0.0029)	(0.0026)	(0.0285)	(0.0014)	(0.0043)	(0.0016)
*NR*Post*	0.0042	-0.0032	-0.2047***	0.0073***	-0.0028	0.0036
	(0.0027)	(0.0024)	(0.0281)	(0.0012)	(0.0041)	(0.0033)
Post	-0.0974***	-0.0564***	-0.2684***	0.0317***	0.1635***	-0.0058***
	(0.0014)	(0.0012)	(0.0125)	(0.0007)	(0.0021)	(0.0011)
Constant	1.3062***	0.6877***	-0.4933***	0.4667***	0.4237***	0.0917***
	(0.0107)	(0.0093)	(0.0951)	(0.0052)	(0.0168)	(0.0080)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	148180	148180	148180	148180	148180	148180
Adjusted R^2	0.4686	0.1487	0.1929	0.2336	0.1836	0.0504

Table 13 Comparison of self-directed portfolios between adopters who review portfolio reports and those who do not

Table 13 compares self-directed portfolios of adopters who review portfolio reports with those who do not for the three quarters following adoption. The analysis includes five aspects: 1) the percentage of the subscription to mutual funds that appear in the adopter's recent BangNiTou portfolio (Panel A); 2) the percentage of the subscription to mutual funds increasingly held by the adopter's recent BangNiTou portfolio (Panel B); 3) the percentage of the redemption of mutual funds reduced by the adopter's recent BangNiTou portfolio (Panel C); 4) the percentage of the subscription of mutual funds managed by fund companies appearing in the adopter's recent BangNiTou portfolio (Panel D); 5) the distance in investment style between the investor's self-directed portfolio and her BangNiTou portfolio (Panel E). Investment style is quantified using a composite index constructed based on the portfolio's factor exposures calculated at the end of the quarter. These factors include the market factor, size factor, valuation factor, momentum factor and industry index. We also report the differences between the two groups of adopters and the corresponding *t*-statistics.

Whether read BangNiTou portfolio report	1st Quarter	2nd Quarter	3rd Quarter
	Panel A: The percentage of the subscription to mutual funds that appear in recent BangNiTou portfolios (%)		
Yes	1.11	1.31	0.74
No	0.92	1.05	0.61
Difference	0.19	0.26	0.13
t-stat	4.81	6.15	3.59
	Panel B: The percentage of the subscription to mutual funds increasingly held by recent BangNiTou portfolios (%)		
Yes		0.73	0.34
No		0.69	0.29
Difference		0.04	0.05
t-stat		3.54	3.67
	Panel C: The percentage of the redemption of mutual funds reduced by recent BangNiTou portfolios (%)		
Yes		0.42	0.16
No		0.22	0.13
Difference		0.20	0.03
t-stat		5.23	2.55
	Panel D: The percentage of the subscription of mutual funds managed by fund companies appearing in recent BangNiTou portfolios (%)		
Yes	33.5	38.3	38.5
No	30.1	33.2	33.4
Difference	3.4	5.1	5.1
t-stat	11.56	15.09	10.92
	Panel E: The distance in investment style		
Yes	274	264	250
No	286	276	264
Difference	-12	-12	-14
t-stat	-10.21	-9.82	-8.81

Table 14 Robo-advising's effect on investors' self-directed portfolio performance

Table 14 examines whether adopters' self-directed portfolios perform better after adoption. The dependent variables are portfolio performance measures, including the *style-adjusted return* in column (1) and (2), *style-adjusted volatility* in column (3) and (4), and *style-adjusted Sharpe ratio* in column (5) and (6). Model (4) is used to examine the change in adopters' self-directed portfolio performance after adoption. Only adopters are included in Model (4). Model (5) is a DiD specification that examines the difference in the change of self-directed portfolio performance after adoption between robo-advising adopters and non-adopters. Column (1), (3) and (5) report results for Model (4) and column (2), (4) and (6) report results for Model (5). The variable of interest in column (1), (3) and (5) is *post*, which captures the difference in performance between the pre- and post-adoption period. The variable of interest in column (2), (4) and (6) is Treat**post*, which captures the difference in performance between the pre- and post-adoption period for adopters relative to non-adopters. All Measures in this table are at the investor-period level. The regression coefficients and standard errors clustered by investors are reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Style-adjusted return		*Style-adjusted volatility*		*Style-adjusted Sharpe ratio*	
	(1)	(2)	(3)	(4)	(5)	(6)
	Model (4)	Model (5)	Model (4)	Model (5)	Model (4)	Model (5)
Post	0.0198***	0.0204***	0.0059***	0.0054***	0.0433***	0.0508***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
*Treat*Post*		0.0096***		0.0014***		0.0033***
		(0.000)		(0.000)		(0.001)
Constant	-0.003***	-0.0046***	0.0017***	-0.0029***	-0.0492***	-0.0877***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)
Investor FE	Y	Y	Y	Y	Y	Y
Obs.	148180	286272	148180	286272	148180	286272
Adjusted R^2	0.1236	0.0875	0.1036	0.1025	0.0519	0.0523

Figure 1 Overview of BangNiTou app

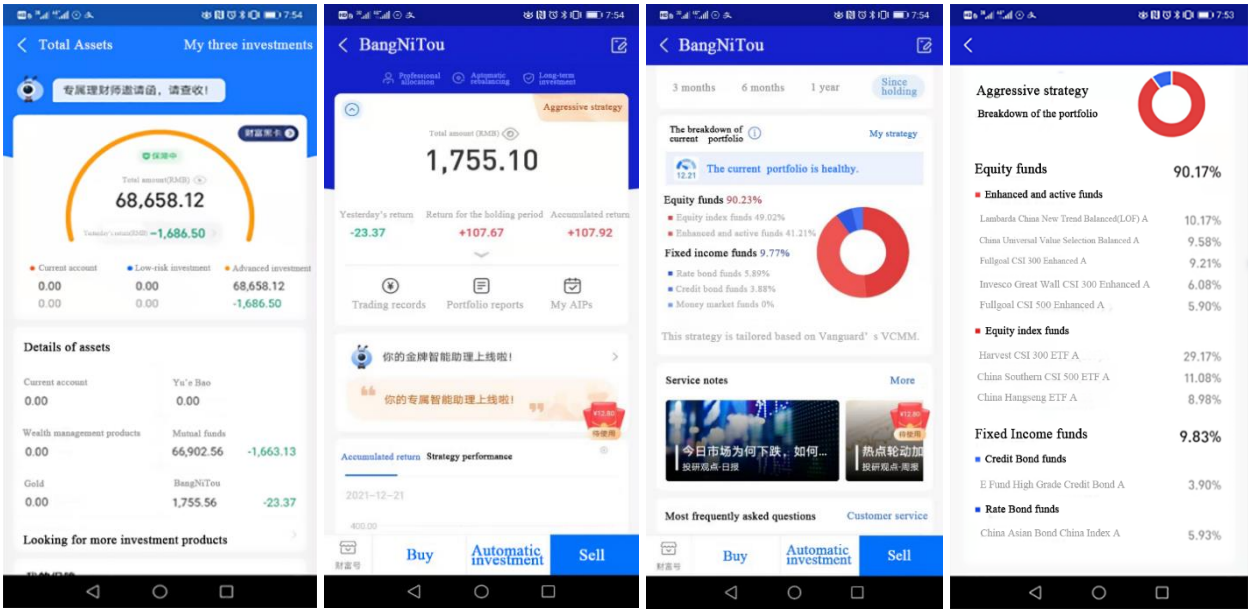


Figure 1 displays the screenshots of the BangNiTou app. The original screenshots were in Chinese, and we provide the translated versions in English for clarity and accessibility. The first screenshot on the left provides an overview of the Alipay user's invested wealth, including money market funds, mutual funds, gold, and the investment delegated to BangNiTou. The investor can overview her total investment amount and daily-updated performance through this page. After clicking "BangNiTou" in the first screenshot, the investor will enter the BangNiTou app as presented in the second screenshot from the left, where investors have access to information including BangNiTou daily performance updates, cumulative return for a certain period, trading records, and quarterly portfolio reports. The third screenshot from the left presents the allocation of BangNiTou portfolio between equity funds and fixed-income funds. Finally, fourth screenshot presents even more detailed portfolio information, including the names of each mutual fund and their shares within the portfolio.

Figure 2 Overview of service notes on BangNiTou App

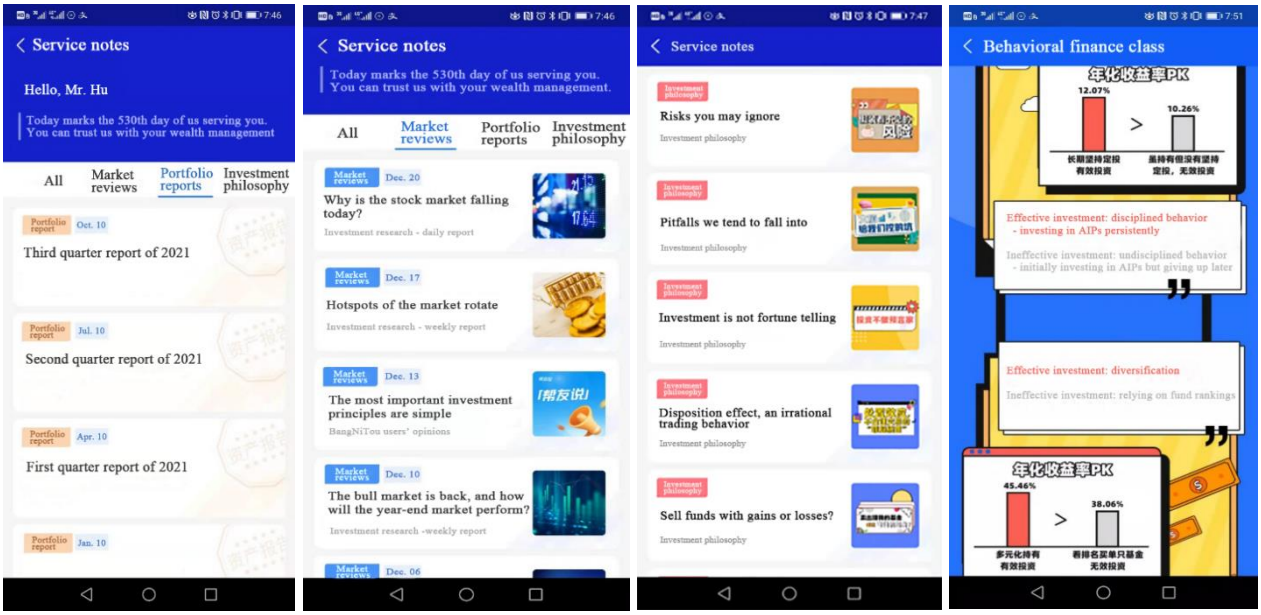
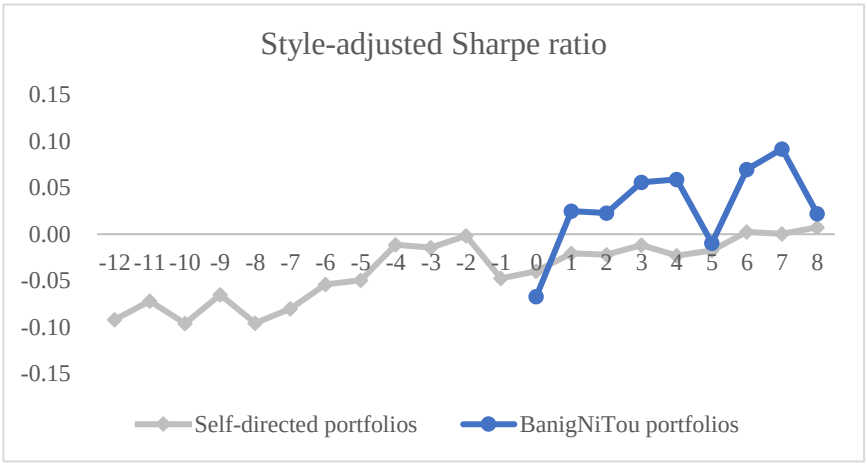
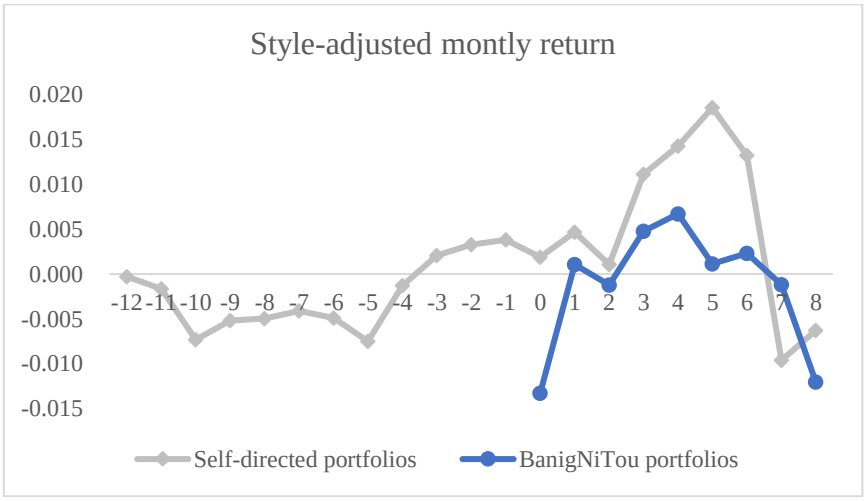


Figure 2 displays the screenshots of the BangNiTou app. The original screenshots were in Chinese, and we provide the translated versions in English for clarity and accessibility. The first screenshot on the left shows quarterly reports for the investor's BangNiTou portfolio. The second screenshot from the left contains articles aiming to aid investors in understanding market fluctuations and managing their emotions. The third screenshot pertains to the "investment philosophy" section, featuring articles that discuss common investment pitfalls, including topics such as investment risks ignored, cognitive traps, and behavioral biases. The fourth screenshot is also within the realm of the "investment philosophy" section, highlighting a learning center that emphasizes behavioral finance, including topics such as the importance of self-discipline in automatic investment plans, diversification and the avoidance of relying on various rankings when phurchasing mutual funds.

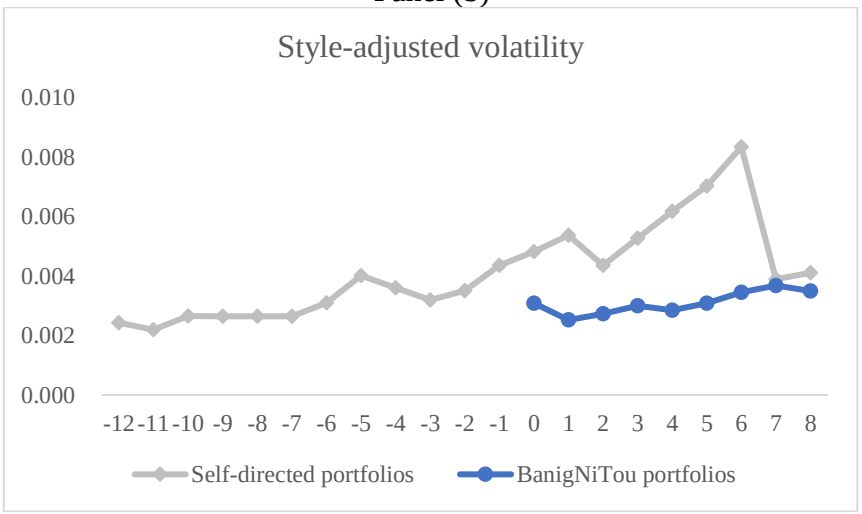
Figure 3 Investment performance: self-directed portfolios vs. BangNiTou portfolios



Panel (a)



Panel (b)



Panel (c)

Figure 3 plots the style-adjusted investment performance for investors' BangNiTou portfolios versus their self-directed portfolios from twelve months before to eight months after robo-advising adoption. Investment performance is measured by the style-adjusted Sharpe ratio (Panel (a)), style-adjusted return (Panel (b)), and style-adjusted volatility (Panel (c)).

Figure 4 Investment behavioral biases: self-directed portfolios vs. BangNiTou Portfolios

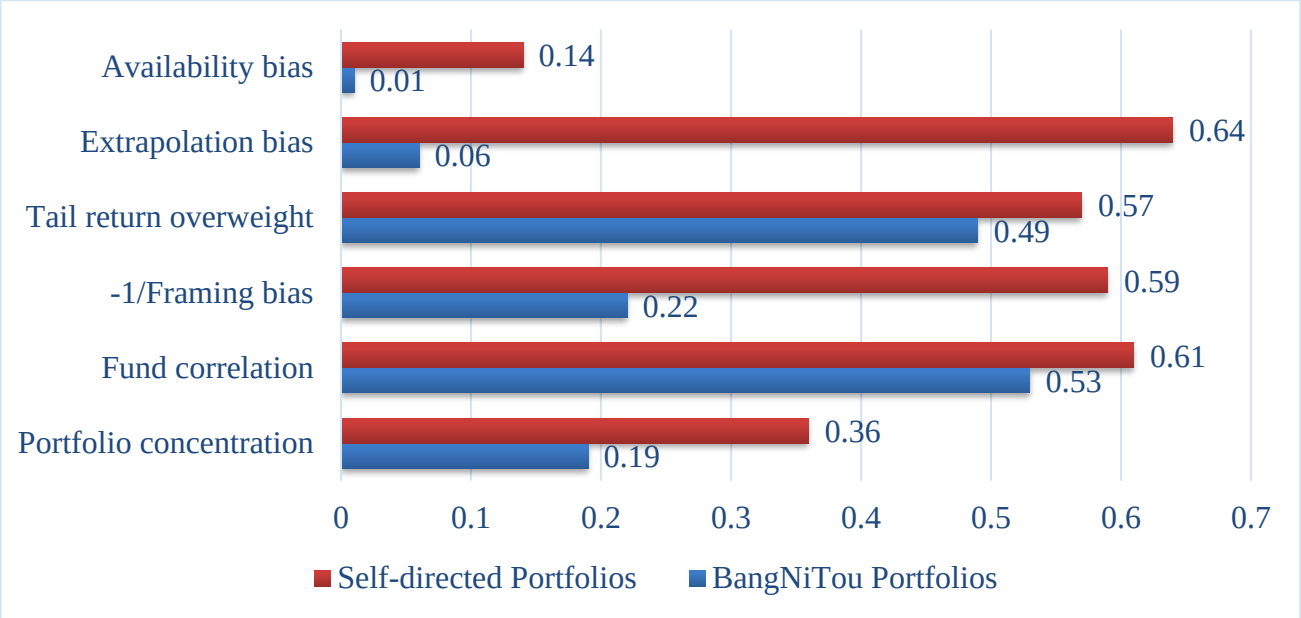


Figure 4 compares the average investment behavioral biases observed in investors' BangNiTou portfolios and their self-directed portfolios over the eight months after the robo-advising adoption.

Figure 5 The economic significance of spillover effects

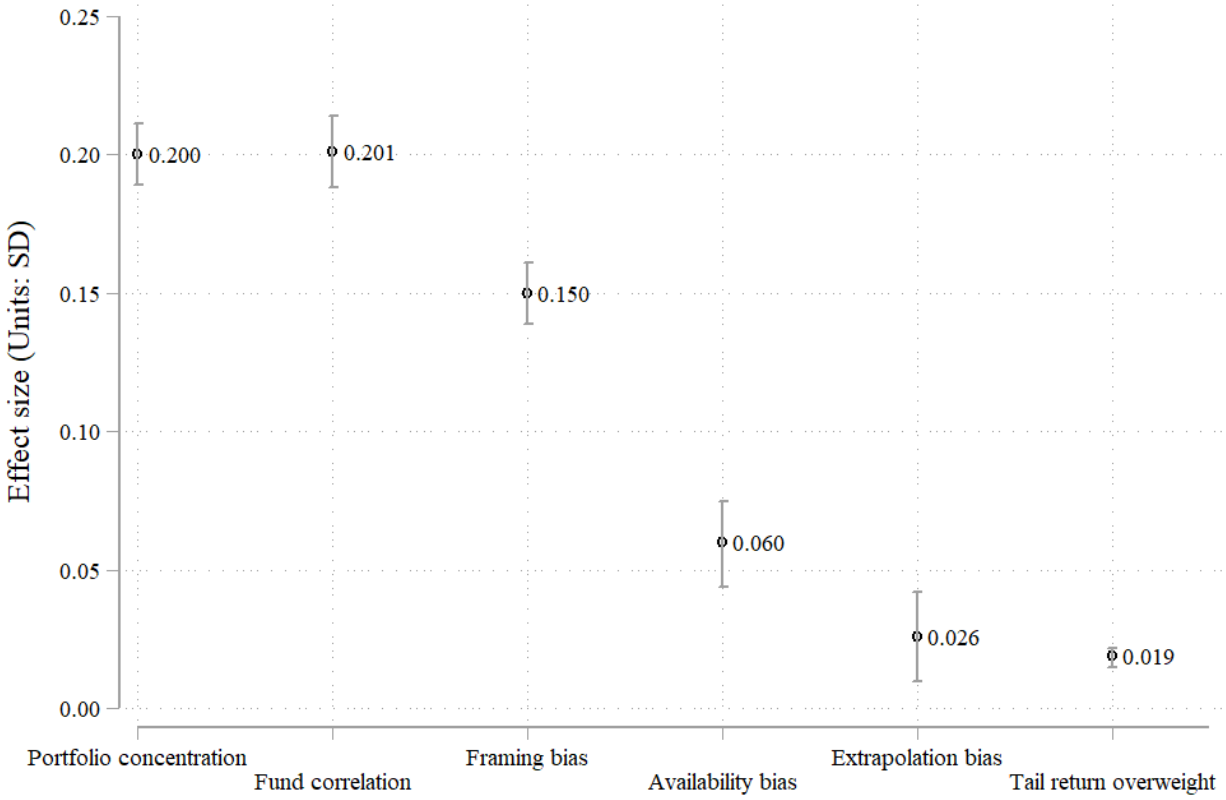


Figure 5 compares the economic magnitude of the education effect on various behavioral biases. The effect size is defined as the estimated coefficient obtained from Model (2), as reported in Table 5 or Table 6, divided by the sample standard deviation of that specific behavioral bias in our sample.