Beyond Performance: The Financial Education Role of Robo-Advising

Rubin Hao
Faculty of Business Administration
University of Macau
rubinhao@um.edu.mo

Conghui Hu
Business School
Beijing Normal University
huconghui@bnu.edu.cn

Xin Xu
School of Finance
Guangdong University of Finance and Economics
xuxinfinance@foxmail.com

Yu Zhang
Ant Group
zhangyu.z@antfin.com

Key words: Robo-advising; household finance; financial education; financial inclusion; fintech; behavior bias; mutual fund sales.

We appreciate helpful comments and suggestions from Shawn Cole, Jiajun Jiang, Baolian Wang, Belinda Yau, Jianfeng Yu, and workshop participants from Fudan University, Huazhong University of Science and Technology, Tianjin University, and Zhongnan University of Economics and Law. We highly appreciate Yixuan Wang and Dongdong Ma from Ant Group for their excellent research assistance. We also thank Likun Qin, Yaogang Zhang, Fang Wang, Shuo Shan, Shu Chen and Zhenhua Li from Ant Group for their help regarding BangNiTou's business details and data processing.

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Abstract

This study examines the impact of robo-advising on personal wealth management based on a unique data set of individual investors' investment accounts. Robo-advising portfolios have better performance, measured as lower volatility and a higher Sharpe ratio, than investors' self-directed portfolios. More importantly, we find evidence that robo-advising has a spillover effect on its adopters: it improves their financial sophistication. Investors have more diversified portfolios and exhibit fewer behavioral biases in portfolio management and fund choices in their self-directed accounts after adopting robo-advising. We use whether investors are exposed to the robo-advisor advertising as the instrumental variable for identification, and our findings still hold in the instrumental variable estimation. The spillover effect is more prominent for adopters who interact with the service more actively and who were less rational before adopting the app. We also find that adopters learn from the robo-advisor by simply imitating its portfolios or strategies. These findings indicate that robo-advising effectively plays a role in educating investors through repeated interactions with its adopters and setting investment models that are easy to follow. Collectively, this study not only solidifies the fact that robo-advising improves investors' investment performance but also provides large-sample, non-laboratory evidence that robo-advising can serve as a financial education tool that improves investor sophistication.

1. Introduction

To obtain a considerable risk premium, households should invest in risky assets; however, many households lack the financial knowledge and skills to comfortably do so. Therefore, households often delegate their investments to financial advisory firms. Traditionally, financial advisory firms hire human advisors to serve their clients and thus are expensive to most households, which results in only wealthy households having access to traditional financial advisory firms. Even when households have access, there are often conflicts of interest between the human advisors and clients (Hackethal et al., 2012; Hoechles et al., 2017, 2018). Human advisors' cognitive limitations and behavioral biases may also cause underperformance (Foerster et al., 2017; Linnainmaa et al., 2021).

Robo-advising, which has become more common over the last decade, is less expensive and requires low opening balances as it relies on digital platforms that provide automated, algorithmic investment services with minimal human involvement. Additionally, robo-advising can largely avoid conflicts of interest and behavioral biases that exist in human advising.[1] Using proprietary data from BangNiTou (meaning "help you invest" in Chinese), which is the largest Chinese robo-advisor and a joint venture of Vanguard and Ant Group, we examine whether robo-advising provides better investment performance for its adopters and whether it makes them more sophisticated.

Prior studies document that robo-advising improves investor welfare by providing low-fee, diversified, and personalized portfolios (e.g., D'Acunto et al., 2019; Rossi & Utkus, 2021; Bianchi & Brière, 2021). This study differs from prior research in two aspects. First, prior studies cannot observe investors' own portfolios after they adopt robo-advising, but we have data on robo-advising adopters' self-directed portfolios both before and after adoption. This advantage allows us to examine whether individual investors' interaction with robo-advising improves their financial

[1] Admittedly, robo-advising tools might be subject to the biases, conflicts, and limitations of the humans and institutions that develop them. However, they are by construction less likely to be influenced by the idiosyncrasies of specific human advisors (Rossi & Utkus, 2021).

sophistication and changes their investment behaviors.[2] In other words, we can investigate whether robo-advising plays a role of financial education. Financial education literature emphasizes the essential role of financial education in equipping naive households with financial knowledge and skills for better financial decisions (e.g., Campbell, 2006, Lusardi & Mitchell, 2014). Kaiser et al. (2022) find that financial education can effectively improve investors' financial knowledge and downstream financial behaviors through a meta-analysis of 76 randomized experiments. They call for future research using administrative data since existing research generally relies on self-reported survey data.[3] This study fills the void by examining how robo-advising changes investor behavior using large-sample data from a real investment platform, where investors are exposed to financial education unintentionally. Survey evidence shows that robo-advising can serve as an empowering tool that improves investor financial literacy (Rossi & Utkus, 2020), and this study examines whether the improvement exists empirically. Additionally, different from existing financial education studies that are more about household saving behaviors, we analyze the effectiveness of financial education on how households invest in risky assets, and more specifically, their portfolio management and fund choices.

Second, although robo-advising lowers advisory fees and is accessible to more households, prior studies find that most robo-advising adopters are still wealthy investors, so it is unclear to what extent the findings of those studies can be generalizable to poorer and less sophisticated investors.[4] By contrast, the majority of BangNiTou subscribers are younger and less wealthy investors. BangNiTou is integrated into Alipay, which initially was the world's largest digital payment platform that penetrated most Chinese households and is now the one-stop "super app" that covers almost all demands of everyday life, ranging from ride-sharing to utility bill payment to mutual fund

[2] Many investors in our sample keep investing in their self-directed accounts after adopting robo-advising, and this data structure allows us to compare investor behaviors before and after adoption through their self-directed accounts so that we can examine whether adopting robo-advising improves investor sophistication.
[3] 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."
[4] This is largely because of the channel through which the robo-advisor is introduced to investors. For instance, Vanguard relies on its existing client base and these clients are generally wealthy.

investment.[5] The entry barriers for signing up for BangNiTou are much lower than all the robo-advisors studied in prior literature.[6] As a result, BangNiTou has a much broader client base and significantly higher portion of poor and young investors than other robo-advisors.[7] According to Campbell (2006), poorer and less educated households are more likely to make investment mistakes, such as underdiversification of risky portfolios, but they are also less likely to seek advice from financial experts (e.g., Hackethal et al., 2012; Collins, 2012). Our data enable us to explore whether robo-advising can improve performance for poor and less sophisticated investors. We also consider whether robo-advising serves to educate younger and smaller investors, who are thought to be less equipped to invest in risky assets and thus need more financial education.

BangNiTou can effectively improve its users' sophistication for two reasons. First, it is difficult for naive investors to retrieve and apply knowledge of basic principles to investment decisions when the education is about knowledge of facts, which is the typical form of education examined by most prior studies (Fernandes et al., 2014). Robo-advising bridges the gap by offering investors specific skills that are easy to follow, such as setting real models of mutual fund portfolios and posting tips about how to specifically allocate their assets. Second, the adopters tend to frequently log in to their BangNiTou accounts to check their portfolio performance, which updates daily, so they are frequently exposed to the content in the app (e.g., portfolio reports and service notes), reinforcing the education effect through repeated interaction between the robo-advisor and its users.

We randomly select 100,000 investors from the population of approximately 1 million investors who registered for BangNiTou from July 2020 through December 2020. Since these adopters invest in BangNiTou through their Alipay account, where we can obtain data on their digital footprints on the BangNiTou app as well as trades and positions for both their BangNiTou accounts and their self-

[5] Alipay claims to have more than 1 billion users globally. These users can access BangNiTou simply by several clicks of the app.
[6] The minimum investment for a BangNiTou subscription is merely RMB 1,000 (about $142). The annual advisory fee rate is 0.5% or below (varying with specific strategies), which is charged daily.
[7] The mean/median of assets for subscribers of BangNiTou is only RMB 67,665/24,272 (about $9,666/3,467). By contrast, in Rossi and Utkus (2021), the median (mean) of subscribers' asset is $282,450 ($588,246), and the bottom decile is below $42,604. The mean (median) investor age is 30.84 (29) year old.

directed accounts, including their investments in mutual funds, money market funds (MMFs), wealth management products (WMPs), and cash. The sample period is July 2019 through March 2021. In the analysis of whether robo-advising improves investor sophistication, we use stratified sampling and the PSM method to construct the matched sample.

We first explore the effects of robo-advising on investment performance by comparing performance between investors' BangNiTou accounts and their self-directed accounts. Investment performance is measured by style-adjusted measures including portfolio return, volatility, and the Sharpe ratio. Portfolios managed by BangNiTou have lower style-adjusted volatility and a higher style-adjusted Sharpe ratio than investors' self-directed portfolios before they adopt the robo-advisor, consistent with the finding in Rossi and Utkus (2021). Both studies suggest that robo-advising improves investor performance mainly through lowering portfolio volatility. Different from Rossi and Utkus (2021), we further document that BangNiTou portfolios perform better than investors' self-directed portfolios in the same period, excluding the possibility that the improvement in portfolio performance after adoption is driven by investors' changing ability or a result of self-selection.

Further analyses indicate that robo-advising performs better than investors' self-directed accounts by holding more index funds, holding more diversified portfolios, and implementing strategies less subject to market fluctuation. Moreover, an important channel through which robo-advising improves investor performance is eliminating behavioral biases in fund choices and portfolio management. Specifically, BangNiTou portfolios display less framing bias, availability bias, extrapolation bias, and tail return overweight than investors' self-directed portfolios. Additionally, we find that investors displaying more tail return overweight, framing bias, and extrapolation bias beforehand benefit more after adopting robo-advising, indicating that overcoming behavioral biases is an important channel through which robo-advising improves investor performance.

Next, we investigate robo-advising's education effect by comparing investment behaviors of BangNiTou adopters and non-adopters. In all specifications, individual investor fixed effects are included to control for time-invariant and unknown investor characteristics. After adopting BangNiTou, investors' self-directed portfolios become more diversified and less subject to framing bias. Additionally, BangNiTou adopters exhibit fewer behavioral biases in fund choices in terms of tail return overweight, extrapolation bias, and availability bias. Interestingly, we document that the economic magnitudes of the changes are significant for portfolio management, equivalent to 15% – 20% of the standard deviation before signing up for BangNiTou, but much less significant for fund choice. Our explanation for the discrepancy is that investors fund choices are affected not only by investor behavioral bias itself but also by the conflicts of interest between fund sales firms and investors: these firms may exploit investors' biases and promote funds catering to investor biases to boost sales and ignoring the funds' expected future performance. Collectively, we find evidence that adopting robo-advising makes investors more sophisticated and less subject to behavioral biases.

The results discussed above cannot control for time-variant unobserved variables. For example, it is possible that robo-advising adopters may learn from another financial education program that improves their financial literacy and promotes investment principles similar to what robo-advising advocates just prior to signing up for BangNiTou, thereby improving their financial literacy. We use BangNiTou's promotional campaign, which randomly selects potential investors in the Alipay app and sends them pop-up ads, as our identification strategy to address the concern of an unobserved omitted variable. Specifically, we use whether the investor is exposed to the advertisement as an instrumental variable (IV) of robo-advising adoption. It is a valid IV because investors' exposure to the advertisement is random and the pop-up ads effectively convert Alipay users into BangNiTou adopters. Our results of IV estimation support that investors have more diversified portfolios as well as less investor behavior bias in portfolio management and fund choices after adopting robo-advising, and the economic magnitude of the IV estimation is even larger than that of the OLS regression. Therefore, our finding that adopting robo-advising improves investor sophistication is unlikely to be driven by selection bias.

Finally, we examine the mechanisms through which BangNiTou improves investors' financial sophistication. Using data on investors' interaction with the BangNiTou app, we find that the education effect is significantly more prominent for investors who are more active users of the app and thus are more intensely affected by robo-advising. Investors may spend time browsing their portfolio performance as well as reading materials posted in the app that impart financial knowledge and investment skills, such as tips on how to diversify one's portfolio or how to avoid chasing momentum. This finding suggests that the repeated interaction between investors and robo-advising is more intense and thus are more likely to change investors' behavior and investment decisions.

We also find evidence that robo-advising changes investor behavior through less difficulty in learning. Investors who have read BangNiTou quarterly portfolio reports hold and buy more funds appearing in their BangNiTou portfolios, buy more mutual funds managed by managers in their BangNiTou portfolios, sell more mutual funds decreasingly held by their BangNiYou portfolios, and the style of their self-directed portfolios is more similar to that of their robo-advising portfolios. Our findings suggest that less difficulty in learning for small investors, such as the easy-to-follow investment portfolios, can effectively change investor behaviors.

2. Related literature and contributions of this study

2.1 Fintech and robo-advising

As fintech has emerged as an important player in the financial sector and has grown sharply over the last decade, academic research on fintech has increased as well. Goldstein et al. (2019) discuss fintech's impact on household finances and financial institutions from the macroeconomic perspective. Carlin et al. (2017) find that the introduction of a particular smartphone app for personal financial management changed consumers' credit use and improved financial fitness. Using administrative and survey data from Kenya, Suri et al. (2021) find that the increase in the availability of digital loans improves household resilience. Chen et al. (2021) use a regression discontinuity design to show a causal relation between access to fintech credit and lower sales volatility and bankruptcy risk for micro, small, and medium-sized enterprises (MSMEs). Closely related to our study, Hong et al. (2021) argue that the rapid increase in the use of online digital payment platforms, specifically, the penetration of Alipay in daily Chinese life, accumulates individuals' trust in fintech firms and thus encourages more risk-taking in household finances. The study relies on instrument variables, such as the distance between Alipay users' residences and Hangzhou—Alibaba's headquarters location—for identification. It does not explore individual-level mutual fund investment behavior.

Research on robo-advising, the main manifestation of fintech in financial advisory firms, is still rare. The first study on robo-advising, D'Acunto et al. (2019), investigates how the introduction of an automated stock portfolio optimizer changes investors' portfolio choices and trade decisions. The study finds that investors better diversify their stock portfolios after adopting robo-advising, with ex ante undiversified investors increasing stock holdings and already well-diversified investors holding fewer stocks. Adopters exhibit declines in prominent behavioral biases, including the disposition bias, trend chasing, and the rank effect. By comparing optimal portfolios and investors' actual portfolios, they introduce the notion that robo-advising can perform a financial educational purpose, but they do not explore exactly how the education works.

The robo-advisor studied in D'Acunto et al. (2019) offers investors portfolio advice and investors can decide whether to follow the advice. Bianchi and Brière (2021) examine a similar robo-advisor introduced by a French fund manager in a large set of employee saving plans. They also find that investors willing to follow robo-advice achieve better investment performance. Different from the two studies, the hybrid robo-advisor in Rossi and Utkus (2021) is Vanguard's Personal Advisor Service (PAS), to which investors fully delegate their asset management once they register. As the world's largest robo-advisor, PAS automatically allocates assets and rebalances portfolios following algorithms designed and coded by its experts; human advisors only explain the plan to investors before they sign up. PAS manages portfolios including stocks, mutual funds, bonds, and cash. PAS fully diversifies investors' portfolios, decreases stock holdings, invests more in index funds that have lower management fees, invest internationally and decrease local exposure, increase the share of risky assets including equity and bond holdings, and decrease cash holdings. As a result, PAS significantly improves investment performance measured by the abnormal Sharpe ratio. Additionally, the improvement in investment performance is significantly greater for those investors with a previous low share of risky assets, with previous low mutual fund holdings, with previous low index fund holdings, and with a lack of investment experience. BangNiTou is a robo-advising tool similar to Vanguard's PAS except that it has a lower entry barrier for subscribers and thus is accessible for a much wider range of households, especially lower-income households.[8] Similarly, we also find that the portfolios managed by BangNiTou have a higher Sharpe ratio and lower volatility, are more diversified, and invest more in index funds than self-managed portfolios.

Our study differs from the existing research in several ways. First, our access to individual account-level data on investors' self-directed portfolios both before and after adopting BangNiTou allows us to focus on the education role of robo-advising and provides us a just-in-time setting to directly examine whether robo-advising can effectively improve investors' financial literacy. We find that investors become more sophisticated after adopting robo-advising, and the improvement is more significant for investors who are more naïve ex ante and later interact more with robo-advising. Second, we examine how robo-advising benefits small investors. Because 80% – 90% of PAS users are clients of Vanguard's traditional financial advisory service and its minimum investment is

[8] Robo-advisors examined in prior studies may vary in the services they provide. The robo-advisor in D'Acunto et al. (2019) is a stock portfolio optimizer, while the robo-advisors in other studies manage assets including stocks, equity and bond funds, and cash holdings. The robo-advisors in D'Acunto et al. (2019) and Bianchi and Brière (2021) offer investors portfolio advice and leave investors to follow or ignore the advice, while the robo-advisors in Rossi and Utkus (2021) and Reher and Sokolinski (2021) only allow adopters to fully delegate the asset management to them. These robo-advisors also vary in minimum investment requirements and human advisor intervention.

$50,000, most PAS robo-advising adopters are not small investors.[9] Reher and Sokolinski (2021) find that lowering the minimum investment of robo-advisors induces more middle-class households to use the advisory service and their investment performance improves thereafter, but lower-income households are not affected by the scheme because they are still excluded from robo-advisors. In contrast, the BangNiTou app is integrated into the Alipay app that has penetrated to roughly one billion users, and it can be accessed with an investment of only RMB 800 to 1,000 (about $114 to $143); therefore, most BangNiTou users are small investors who are regarded as having the lowest financial literacy. The low investment barrier of BangNiTou allows us to examine whether and how robo-advising can be beneficial to small investors who have little access to traditional financial advisory services. The answer to this question has important implications on how fintech can promote financial inclusion. Third, prior studies such as Rossi and Utkus (2021) must construct a control sample of non-adopters to illustrate how robo-advising improves investors' portfolio performance to control for the observed differences between the robo-advising adopters and non-adopters, but since we can directly observe both the adopters' account holdings in BangNiTou and their holdings in self-directed investment accounts, we can provide more robust and convincing evidence on whether robo-advising generates better performance. Fourth, Rossi and Utkus (2021) emphasize robo-advising's beneficial impact of portfolio diversification and index fund investing, and Bianchi and Brière (2021) emphasize the importance of portfolio rebalancing. Our study further finds that robo-advising improves investor performance by avoiding investors' behavioral biases in fund choices.

2.2 Financial education

According to the household finance literature, individuals with higher financial literacy are more able to invest in capital markets, have high stock market participation (Van Rooij et al., 2011), have more diversified portfolios (Calvet et al., 2007; Gaudecker, 2015), have better portfolio

[9] https://www.investopedia.com/vanguard-personal-advisor-services-review-4692536

rebalancing (Guiso & Vivano, 2015; Bianchi, 2018), and have better investment performance (Gaudecker, 2015; Bianchi, 2018). As a result, both academic researchers and policymakers advocate for financial education to improve households' financial literacy so that they can benefit from financial services (Lusardi, Michaud, & Mitchell, 2017).

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 and investment behaviors (e.g., Drexler et al., 2014; Skimmyhorn, 2016; Song, 2015). For instance, using a natural experiment of a personal financial management course in the US Army, Skimmyhorn (2016) finds that the course substantially increases retirement savings rates and average monthly contributions. A field experiment study by Song (2015) randomly assigned households in rural China to a financial education treatment emphasizing the concept of compound interest and found the treatment increased pension contributions by roughly 40%.

Other studies cast doubt on the effectiveness of financial education in improving literacy. Studies find there is a gap between financial knowledge and behavior change: financial decision making such as savings and investment is sophisticated, so it is quite challenging to help people function more effectively through simply obtaining more financial knowledge (Cole et al., 2011; Willis, 2013; Fernandes et al., 2014; Lusardi & Mitchell, 2014; Carpena et al., 2019). Fernandes et al. (2014) conduct a meta-analysis of 168 papers covering 201 prior studies of the relationship of financial literacy and financial education to financial behaviors and find that financial education has a very modest effect on financial behaviors, with even lower effects on low-income households. They propose two possible reasons for the weak effect. First, financial education explored by existing studies is more about content knowledge rather than financial skills, and investors find it difficult to translate knowledge into investment decisions. Second, the education effect decays over time. Therefore, the authors suggest future studies to explore a real but narrower role for just-in-time financial education tied to specific behaviors it intends to help. Robo-advising is such an education setting that fits the suggested features well. Survey evidence show that robo-advisors can serve as an empowering tool that improves their clients' financial literacy (Rossi & Utkus, 2020). The educational effect of robo-advising pertains to techniques specifically about how to improve one's portfolio performance. Robo-advising is "just-in-time" in that we examine the short-period effect right before and just after investors adopt the service.

In contrast to Fernandes et al. (2014), another meta-analysis paper by Kaiser et al. (2022) summarizes 76 more recently published experimental studies and shows that financial education programs have, on average, positive causal treatment effects on financial knowledge and downstream financial behaviors. 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. Our study fills the void by using the large-sample, individual account data of BangNiTou subscribers. More importantly, the majority of BangNiTou users are lower-income and younger households. This feature of our data ideally fits the purpose of financial education—to improve the sophistication of small and naive investors who have extremely limited access to traditional financial advisory services. We contribute to the financial education literature by showing that robo-advising effectively improves investors' skills in portfolio management and fund choice. Additionally, we find that the repeated interaction between robo-advising and its adopters and the easy-to-follow portfolio models contribute to the positive educational effect.

2.3 Financial advisory firms

Existing literature as mixed evidence on whether traditional financial advisory firms provide better investment performance for their clients (Shapira & Venezia, 2001; Gaudecker, 2015; Kramer, 2012; Hackethal et al., 2012; Mullainathan et al., 2012). Using proprietary individual trade-level data, Hoechles et al. (2017) find that financial advisors hurt trading performance as they tend to advise trades following financial analysts' calls and buy stocks with extreme positive returns in the recent past, although they help reduce some of the behavioral biases retail investors are subject to.

As do Rossi and Utkus (2021), we find that robo-advising portfolios perform better with significantly higher Sharpe ratios, suggesting that robo-advising can more effectively improve investment performance than traditional financial advisors. Furthermore, we find that robo-advising can better rebalance portfolios, exhibit less extrapolation bias, availability bias, and tail return overweight in fund choices. In contrast, traditional human financial advisors are criticized for displaying behavioral biases in fund choices and inducing too many trades due to human advisors' self-interest. Therefore, our findings reveal that robo-advising creates value for its clients by avoiding human behavioral biases and conflicts of interest.

3. BangNiTou

BangNiTou is a joint venture of Vanguard and Ant Group; its robo-advisor launched in April 2020. It is the Chinese counterpart of Vanguard's PAS, 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 covers almost all everyday demands people have, 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. Figure 1 presents the detailed steps by which Aplipay users can access BangNiTou in the Alipay app.

[Insert Figure 1 Here]

Following D'Acunto and Rossi (2021), we describe BangNiTou in four dimensions:

Personalization of advice: Robo-advisors vary dramatically on the extent to which they can create individually designed investment portfolios and financial plans. Similar to US commercial robo-advisors such as Wealthfront, Betterment, and Vanguard's PAS, BangNiTou tailors investment strategies based on a set of demographic characteristics and risk preferences including their willingness to take financial risk, investment horizon, and income bracket. The robo-advisor studied in D’Acunto et al. (2019) adds individuals’ existing portfolio allocations to the inputs used to generate optimal weights for portfolio allocations, but neither PAS nor BangNiTou uses this design.

Investor involvement: A second aspect that distinguishes different types of robo-advisors is investor involvement. The robo-advisors in D’Acunto et al. (2019) and Bianchi and Brière (2021) ask investors to approve every trading decision before it is executed. In this way, investors can modify the course of action the algorithm suggests and require a re-optimization of their financial plan and strategy at any point. Similar to Vanguard’s PAS, BangNiTou is at the other end of the spectrum. It not only provides automatically generated financial plans and strategies but also places trades automatically on behalf of investors without asking for authorization.

Investor discretion: Discretion is the investors’ ability to override a robo-advisor’s recommendation. There is no investor discretion for some robo-advisors such as Wealthfront and Betterment, which fully automate the implementation of strategies. At the other end of the spectrum is the stock portfolio optimizer studied in D’Acunto et al. (2019) in which the investor has full discretion to adjust the portfolio recommended by the robo-advisor. BangNiTou is in the middle: when a subscriber registers, BangNiTou recommends an investment strategy meant to fit his or her needs, but it leaves it to the subscriber to decide whether to follow the recommendation or switch to an alternative one; the deviation is restricted to the extent that the expected return must be within the range of 2.5% – 12%; additionally, investors will be warned of the deviation from their risk preferences and its potential consequences.

Human interaction: The last differentiating feature among robo-advisors is the degree of interaction investors have with human advisers, if any. Robo-advisors that cater to a wealthier and older clientele are hybrid in nature: the majority of the heavy-lifting in terms of designing the portfolio allocation is performed by the algorithm, but human advisers interact with the investor at key moments, such as at sign-up as well as when investors have important questions about their portfolios. Human advisers' presence is crucial to ensure customers' needs are being satisfied, especially in periods of bear markets, when investors may become more fearful and may wish to reduce their exposure to risk. Similar to Wealthfront and Betterment, BangNiTou is purely automated and investors cannot access any face-to-face communication with human advisors. Not employing human advisers allows such robo-advisors to maintain low operating costs. Fully automated robo-advisors cater to younger cohorts such as millennials, who are generally comfortable with having their wealth managed by algorithms.

BangNiTou regularly provides service notes in its app to partially replace human advisors' function. Service notes include not only quarterly asset reports, whereby investors can obtain details of portfolios and their performance but also articles aiming to improve investor financial literacy (e.g., how to diversify one's portfolio, what behavioral biases investors are prone to and how to avoid these biases). Survey evidence suggests that investors hire financial advisory firms not only for higher returns but also for self-improvement and to acquire peace of mind (Rossi and Rutkus, 2020), so service notes also include materials that give investors peace of mind (e.g., tips on how to manage one's mood in the market turmoil). Figure 2 presents 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 subscribers from the population of approximately 1 million investors who adopted BangNiTou from July 2020 to December 2020. For the control group, using stratified sampling based on demographic characteristics including gender, age, city of residence tier, and amount of assets, we select 300,000 investors from Alipay users that had purchased mutual fund though Alipay but did not adopt

BangNiTou.[10] Then we construct a 1:1 control group using the PSM method based on investment behavior characteristics.

Stratified sampling is implemented as follows. We label the number of BangNiTou adopters as of March 31, 2021, as M and the number of non-adopters as N. We evenly distribute all the investors into 120 groups based on gender, age, city tier, and average assets during April and June 2020 (two groups for gender, two groups for age, three groups for city tier, and ten groups for amount of assets). We then randomly select $100000/M \times m_i$ adopters and $300000/N \times n_i$ non-adopters from group i, with i ranging from 1 to 120, and m_i (n_i) representing the number of adopters (non-adopters) in group i.

Then we construct the control group by conducting the PSM and selecting the most similar non-adopters from the 300,000 Alipay users. The PSM is conducted based on a series of investor characteristics over the 12 months before subscribing BangNiTou, including the amount of assets, 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 funds' return in the portfolio, portfolio return skewness, framing effect, extrapolation bias, availability bias, turnover, and trading frequency. The matching is without replacement.

The sample period is from July 1, 2019, to March 31, 2021. We start the sample construction by randomly selecting 100,000 investors from the population of all BangNiTou adopters and 300,000 investors from the population of Alipay users not adopting the robo-advisor. To construct measures for investment behaviors, we require investors to have: (1) fund investment records for at least three months; and (2) at least three transactions both before and after adopting the robo-advisor. After this

[10] We use stratified sampling to obtain a control group with the demographic characteristics most similar to the treated investors. Alipay has a much broader client base than BangNiTou, and investors using the Alipay app vary in their demographic characteristics and wealth. It is possible that certain groups of them are more likely to adopt BangNiTou, so stratified sampling can make sure that we have enough control group investors to match.

procedure and dropping observations with missing control variables, we end up with 74,090 adopters in our sample. Then we construct a 1:1 matching sample by selecting the most similar control group from the 300,000 non-adopters based on their portfolio characteristics and trading behaviors before signing up. See Table 6 for more details of the matching procedures. Definitions of variables are presented in the Appendix.

4.2 Descriptive statistics

Table 1 presents descriptive statistics of the characteristics of BangNiTou adopters during the twelve months prior to their adoption. Of the adopters, 29.6% are female, which is lower than the 47% female investors in Vanguard's PAS; 58.7% of investors reside in the 14 largest cities. The mean (median) age is 30.84 (29), far below the ages of robo-advising adopters in the United States (63), France (48), and India (48), and more than half of the adopters are between 25 and 35 years old, suggesting that most robo-advising users in our study are younger. The mean of the amount of the adopter's assets is RMB 67,665 ($10,572), far lower than the $588,246 of Vanguard's PAS adopters. The median of their assets is RMB 24,272 ($3,792), well below the median amount of $282,450 in for Vanguard's PAS. The mean (median) of adopter's investment size in Rehery and Sokolinski (2021) is $265,210 ($100,000) even after the robo-advisor lowered its minimum investment. Therefore, the robo-advisor adopters in our study are significantly younger, small investors with much less assets under management.[11] This demographic feature of investors allows us to explore whether robo-advising effectively improves performance for small investors who previously had limited access to traditional financial advisory firms. It also augments our conclusion on the effectiveness of financial education: our findings that poorer and younger investors become more sophisticated after adopting and interacting with the robo-advisor make important contribution to the financial education literature.

[11] 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).

Table 1 shows other characteristics of BangNiTou adopters. The proportion of wealth in money market funds (Yuebao in Aplipay) and wealth management products (WMPs) is higher than 58%, and mutual funds account for about 40% of the wealth.[12] The average monthly investment in mutual funds is RMB 23,327 (about US $3,332), and the average number of fund holdings is 6.8. Of the fund holdings, 26.5% are debt funds, 70.4% are equity funds, and 28.8% are index funds. The monthly frequency of fund subscription and redemption is 7.58. The monthly average amount of fund subscription (redemption) is RMB 8,330 (6,595), and the monthly average turnover is 129.8%. These investment characteristics suggest that investors are financially naive and tend to invest more in low-risk instruments (including MMF and WMPs) and trade funds too frequently.

[Insert Table 1 Here]

Table 2 reports descriptive statistics on investors' accounts in the eight months after subscribing to BangNiTou, including both self-directed accounts and the accounts delegated to the robo-advisor. The average investment increases dramatically to RMB 113,087, suggesting that Alipay users generally invest more through the Alipay app over the sample period, which is consistent with the fact that fintech giants are increasingly penetrating household wealth management. Investors increase their mutual fund investment, with the share of mutual fund holdings changing from 39.7% to 47% and the amount of funds invested incresing from 6.78 to 12.46 during the sample period. The share of debt funds in total mutual fund investment drops to 15.1%, while the share of equity funds in total mutual fund investment rises to 80%. The share of index funds in total mutual fund investment drops slightly from 28.8% to 26.1%. The monthly frequency of fund subscription and redemption rises to 12.65, but the monthly average turnover drops to 90.2%.

The mean (median) amount of assets delegated to BangNiTou is RMB 4,584 (1,026), which is 6.45% (2.39%) of the total investments in Alipay, suggesting that on average, investors regard

[12] Yuebao is the largest money market fund in China. It is operated by Ant Group and all Alipay users can invest in Yuebao after several simple clicks. Since Alipay penetrates into almost every household in China, Yuebao has an extremely broad user base. WMP is an off-balance-sheet substitute for deposits that is widespread in China (Acharya et al, 2021). It is issued by commercial banks and features investment return and risk slightly higher than deposits but much lower than mutual funds.

BangNiTou as part of their portfolio and they allocate only a small portion to it. The median of BangNiTou account turnover is 44.7%, which is lower than the median of investors' self-directed account turnover. Adopters have full access to all the content in the BangNiTou app, which makes it possible for the robo-advisor to play a financial education role. The average number of monthly BangNiTou logins is 16.7, and the average length of time spent in BangNiTou is 160.5 seconds per month, suggesting that adopters do frequently log in and browse the content presented in the app.

[Insert Table 2 Here]

5. Main results

This section reports empirical results for the direct effect and spillover effect of robo-advising. The direct effect refers to whether robo-advising produces better investment performance than investors' self-directed accounts. The indirect effect refers to the financial education effect, namely, whether interacting with robo-advising changes investor behaviors and improves their financial sophistication.

5.1 **The direct effect of robo-advising: investment performance**

5.1.1 Robo-advising on investor performance

We investigate the direct effect by comparing robo-advising portfolio performance with adopters' self-directed portfolio performance both before and after BangNiTou subscription. Prior studies (e.g., D'Acunto et al., 2019; Rossi & Utkus, 2021) only compare performance of robo-advising portfolios with adopters' self-directed portfolios before adoption and non-adopters' self-directed portfolios in the meantime because data on investors' self-directed accounts are not accessible in these studies. As a result, selection bias is a concern: it is possible that robo-advising adopters are investors with worse performance before adoption. Moreover, the better robo-advising performance could be a result of time-variant investor ability: robo-advising adopters may improve their financial literacy and investment skills at the same time as they adopt robo-advising, so the better performance may overstate the positive effect.

We measure performance from three dimensions: investment return, volatility, and the Sharpe ratio. All measures are based on individual account data and are aggregated at the monthly level. Volatility is the standard deviation of portfolio daily return of 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 different portfolio styles and over time, we rely on style-adjusted measures to exclude the effect of time and portfolio style. Specifically, we first calculate the market-wide average performance for equity funds and debt funds, respectively, and then calculate the benchmark performance for the style as the weighted-average performance of the debt and equity fund portfolios, with the investor portfolio as the weight. The style-adjusted return/volatility/Sharpe ratio is calculated as the raw value of return/volatility/Sharpe ratio minus the portfolio style return/volatility/Sharpe ratio.

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 adopting the robo-advisor. The significantly negative style-adjusted Sharpe ratios of investors' self-directed accounts for both pre- and post-adoption periods indicate that 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 perform better than investors' self-directed accounts of the same period (of the period before adoption), suggesting that the robo-advising 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 improves investment performance, measured as the Sharpe ratio, mainly through lowering portfolio volatility. These findings echo and reinforce the conclusion of Rossi and Utkus (2021) by showing that robo-advising portfolios perform better than investors' own portfolios both before adoption and during 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), suggesting that robo-advisors are also beneficial to small investors who are more naive and have more limited access to financial advisory services.

[Insert Table 3 Here]

Figure 3 depicts the trend of portfolio performance for BangNiTou accounts and investors' self-directed accounts over the period of twelve months before and eight months after signing up for the robo-advisor. In each subfigure, time "0" represents the month when clients adopt the robo-advisor. The style-adjusted Sharpe ratio of BangNiTou accounts is higher than that of the adopters' self-directed accounts in almost every month after adoption. The style-adjusted volatility of BangNiTou accounts is lower than that of the adopters' self-directed accounts in almost every month after adoption, and the investment return of the robo-advising is also lower than that of the adopters' self-directed accounts, reinforcing our conclusion that robo-advising improves investment performance mainly though lower portfolio volatility than investor self-directed portfolios. The robo-advisor can effectively lower the portfolio risk and help investors invest better in risky assets.

[Insert Figure 3 Here]

5.1.2 Robo-advising and portfolio changes

This section compares robo-advising portfolios and investors' self-directed portfolios to explore how robo-advising improves investor performance. As reported in Figure 4, Panel (a), robo-advising increases investment in index funds to more than 60% of the mutual fund holdings, compared with about 30% of the fund holdings in investors' self-directed accounts. Many actively managed mutual funds cannot outperform index funds (Sharpe, 1991; Pederson, 2018), especially net of the fund management fee, and small investors have little expertise in fund choices, so investing in low-management-fee index funds are beneficial to small investors.

According to Panels (b) and (c), the robo-advisor lowers the percentage of equity funds in mutual fund holdings from about 70% – 80% to about 60%, and raises the percentage of debt funds from roughly 20% to 40%. Now that BangNiTou tailors investment strategies after considering investors' risk preferences, investors in Alipay seem to invest excessively in equity funds and the robo-advisor corrects the tendency by lowering the portfolio risk on average. Additionally, BangNiTou accounts' percentage of equity fund holdings is stable over time, while it fluctuates more in self-directed accounts, suggesting that investors are more likely to be affected by the market mood while robo-advising portfolios are more immune to it.

[Insert Figure 4 Here]

5.1.3 Robo-advising and investment behaviors

Behavioral finance and household finance literature point out that behavioral biases are an important reason that individual investors incur loss (Bailey, Kumar & Ng, 2012; Barber & Odean, 2013; Beshears et al., 2018). Robo-advising manages portfolios following algorithms and is meant to be able to avoid behavioral biases. In this section, we investigate behavioral biases in fund choices, portfolio management, and rebalancing, three aspects that are more likely to be improved by the robo-advisor and be less affected by investor discretion.[13]

Prior literature documents that individual investors underdiversify their portfolios (e.g., Goetzmann & Kumar, 2008). We measure the extent of diversification of mutual funds held in the portfolio by the Herfindal index and the correlation in fund returns. Specifically, if the ratio between

[13] 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 trading for lottery) (Kumar, 2009; Akbas & 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 examine the behavioral biases of the disposition effect and overtrading, because BangNiTou adopters have the discretion to quit the service at any time.

the value of 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 correlation in fund returns is constructed as follows: we regress each fund's daily return on the portfolio's daily return to obtain the R^2 of the regression; we then use the weighted average of R^2 for all funds in the portfolio as the correlation measure for the portfolio. The higher the correlation measure, the less the portfolio is diversified.

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 there is individual asset trading and the higher the framing bias.

We also include behavioral biases in fund choices, including availability bias (Barber & Odean, 2008; Barber et al., 2021), extrapolation bias (Greenwood & Shleifer, 2014; Da et al., 2021) and tail returns overweight (Kumar, 2009). Availability bias refers to the pattern that investors tend to invest in assets that are attention-grabbing, such as 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 is ranked in top 10% of 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 recent experience and project that it will continue. As a result, investors tend to 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 is the tendency for investors to overweight the probability of extreme positive returns. These investors tend to invest in mutual funds with positively skewed returns. We first calculate the lottery score over the last six months for each mutual fund following 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 5 presents the difference in behavioral biases between robo-advising portfolios and the adopters' self-directed portfolios of the same period. The robo-advisor displays less behavior bias in all dimensions in the figure, including availability bias, extrapolation bias, tail return overweight, framing bias, and underdiversification. The improvement is more prominent in availability bias, extrapolation bias, and framing bias.

As reported in Table 4, BangNiTou portfolio HHI and average correlation in fund returns are significantly lower than the adopters' self-directed portfolios both before and after the robo-advising sign up, suggesting that the robo-advising further diversifies portfolios, 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).

Robo-advising portfolio dynamics are less affected by framing bias as evidenced by the lower framing bias of robo-advising portfolios than self-directed portfolios both before and after adoption. Bianchi and Brière (2021) point out that robo-advising improves investor performance through rebalancing, and our evidence further suggests that the rebalancing displays less framing bias.

Table 4 also shows that robo-advising is less subject to the three types of behavioral biases in fund choice, namely, extrapolation bias, availability bias, and tail return overweight, compared to investors' self-directed accounts both before and after adoption. These behavioral biases are also exaggerated by brokers' marketing strategies that usually cater to investors and promote mutual funds that have recently outperformed or that have extremely high historical returns. In contrast, robo-advising manages portfolios automatically following algorithms that are unlikely to be affected by investor behavioral biases.

[Insert Figure 5 Here]

[Insert Table 4 Here]

5.1.4 Who benefits from adopting robo-advising?

This section explores who benefits from adopting robo-advising. Specifically, we examine how the positive effect of robo-advising on investor performance varies with investor demographic characteristics, ex ante portfolio characteristics, and behavioral biases. We regress the change in portfolio performance on investor demographic characteristics, ex ante portfolio characteristics, and behavioral biases. The dependent variable is the difference between the investor's BangNiTou account's monthly Sharpe ratio and her self-directed account's monthly Sharpe ratio. The higher the difference, the more improvement in investor performance. The independent variables are: investor demographic characteristics, including gender, age (born after 1990 or not), city (large city or not); Alipay account characteristics, including total wealth in Alipay, the ratio of the value of equity funds to total wealth, the ratio of the value of index funds to total wealth; behavior characteristics, including the portfolio Herfindal index, framing bias, tail return overweight, extrapolation bias, availability bias, and portfolio turnover; robo-advising account characteristics, including month of adoption, portfolio strategies, sign-up channels, value of the robo-advising portfolio, and the share of the BangNiTou account in the investor's Alipay account. Variables of portfolios and investment behaviors are the average of the 12 months prior to sign up.

Table 5 reports the results. It presents regression results for specifications that include investor demographic characteristics only (Column 1), Alipay account characteristics (Column 2), mutual fund portfolio characteristics (Column 3), BangNiTou account characteristics (Column 4), and all variables above (Column 5), respectively. Investor demographic characteristics generally are unrelated to the change in investor performance. The coefficient of log(wealth) is significantly negative, suggesting that small investors on average benefit more after adopting robo-advising. The coefficient of the ratio of equity funds to total wealth varies with different specifications.

The coefficients of framing bias, tail return overweight, and extrapolation bias are all significantly positive in both Column (3) and Column (5), indicating that investors displaying more behavioral biases ex ante benefit more after adopting robo-advising. It means that mitigating investor behavioral bias is a crucial mechanism by which robo-advising improves investor performance. The coefficient of availability bias in Column (3) is significantly negative but insignificant in Column (5). The significantly positive coefficient of account turnover suggests that investors trading more can benefit more from adopting robo-advising.

[Insert Table 5 Here]

5.2 The financial education effect of robo-advising

This section analyzes whether and how robo-advising improves adopters' financial sophistication. The survey study by Rossi and Utkus (2020) shows that robo-advisors can serve as an empowering tool that can improve investor financial literacy. We believe BangNiTou works as a powerful education tool based on two features. First, the financial education considered in prior literature is more about investors gaining financial knowledge, but investors, especially naive investors, having difficulty applying the knowledge to their financial decisions (Fernandes et al., 2014). In contrast, robo-advising, as an education tool, is less about general knowledge and more about how to manage one's mutual fund portfolio. BangNiTou regularly updates portfolio reports and strategies in its app and adopters can access the detailed portfolio information at any time. It sets models of mutual fund portfolios that are easy for investors, especially naive investors, to follow. Moreover, the BangNiTou app posts articles on investment guidance that can help investors improve their investment skills in the form of service notes, which include, for instance, information on how to diversify one's portfolio, how to balance risk and return, behavioral biases, and how to avoid investment mistakes. The app also posts articles that help soothe investors' anxiety, stress, and depression after market turmoil to improve their mental well-being and avoid irrational trading.

Second, the robo-advisor intensifies its education effect through repeated interaction with investors. The effect of investor behavior interventions decays over time (Fernandes et al., 2014), so repeated interaction can reinforce it. BangNiTou users frequently log in the app (on average, 17 times per month), monitor the performance of their portfolios and compare it with that of their self-directed accounts, browse the content in the app, including tips and articles posted in the service notes. Both portfolio performance and service notes can contribute to the change in investor behaviors and decision making. The robo-advising portfolio performance, especially compared with their own portfolios, can convince investors to learn from robo-advising, and the effect can be reinforced during each app login. Service notes improve financial literacy by continuously posting articles that highlight important investment skills in the BangNiTou app, and investors are exposed to these highlights each time they log in. The effect is especially stronger for the younger tech-savvy investors who trust fintech and rely on online platforms to improve their financial literacy (Hong et al., 2021).

5.2.1 Regression model

We examine the robo-advising's 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. *Post* is defined as 1 for observations after the sign-up, and 0 otherwise. The monthly observations used in the previous sections of the study are averaged into the investor-period level for this specification. 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:

$$DepVar_{i,period} = a + \beta_1 post_i + \beta_2 Treat_i + \beta_3 Treat_i \times post_i + \gamma control_{i,period} + v_i + e_{i,period}. \tag{2}$$

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 behavior. This specification further controls for factors that affect both the treatment and control groups. Individual investor fixed effects are included in all specifications. Details of variables in each specification are as follows.

In the portfolio diversification test, we use the Herfindal index of the investor's mutual fund portfolio and the average correlation in return as the dependent variable, respectively. We control for variables including the size of wealth, style-adjusted portfolio return, style-adjusted volatility, the share of equity funds in wealth, framing bias, tail return overweight, extrapolation bias, availability bias, and portfolio turnover.

In the portfolio management test, the dependent variables are framing bias and portfolio turnover. We control for variables including the size of wealth, style-adjusted portfolio return, style-adjusted volatility, the share of equity funds in the wealth, HHI, the average return correlation of the portfolio, tail return overweight, extrapolation bias, and availability bias.

In the behavioral bias test, the dependent variables are tail return overweight, extrapolation bias, and availability bias. We control for variables including the size of wealth, style-adjusted portfolio return, style-adjusted volatility, the share of equity funds in the wealth, HHI of the portfolio, framing bias, and portfolio turnover.

5.2.2 Empirical results

Table 6 presents results for the Probit model of which characteristics determine robo-advising adoption. The dependent variable is whether the investor signs up for BangNiTou; independent variables include investor and portfolio characteristics within the 12 months before signing up for robo-advising. Demographic characteristics, such as gender, age, and city of residence should affect investors' decisions to adopt robo-advising, but we cannot analyze these characteristics in the determining test because they are used in the stratified sampling.

Table 6, Column (1) shows that investors whose self-directed mutual fund portfolio performance is better (higher style-adjusted Sharpe ratio and portfolio return and lower style-adjusted portfolio return volatility) are more willing to adopt robo-advising. Analysts 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 less behavioral bias are more likely to adopt robo-advising. Additionally, investors who trade more frequently and those who have more tail return overweight are more likely to adopt robo-advising.

[Insert Table 6 Here]

Contrary to our findings, evidence in the United States seemingly suggests that investors who are more naive are more likely to adopt robo-advising. Rossi and Utkus (2021) document that investors whose self-directed accounts perform poorly are more likely to adopt robo-advising. Reher and Sun (2019) find that investors who underdiversify their portfolios ex ante are more likely to sign up for and invest more in robo-advising after the robo-advisor lowers the minimum investment. Investors' demographic characteristics may be one explanation for the discrepancy between US evidence and our findings. Because BangNiTou is integrated into the Alipay app—the super app that penetrates almost every household in China—it is accessible to a large number of small investors who are less financially literate and who have limited access to human financial advisory firms. As a result, investors with more financial knowledge are aware of the importance of financial advising and take advantage of it.

Table 6, 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 portfolio and investment behavior characteristics after the matching process.

Table 7 reports regression results for the robo-advisor's effect on investor portfolio management. Individual investor fixed effects are included in all specification. The coefficients of $post_i$ in Columns (1), (3), and (5) are significantly negative, indicating that the adopters' mutual fund portfolios are more diversified and display less framing bias after interacting with the robo-advisor. The significantly negative coefficients of the interaction term $Treat_i \times post_i$ suggest that compared with the control group of non-adopters, investors' portfolios are more diversified and display less framing bias after adopting robo-advising.

We evaluate the economic magnitude of the financial education effect using the thresholds proposed by Kraft (2020): less than 0.05 standard deviations 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 significant. For instance, the coefficient of post in Column (1) is −0.083 (significant at the 1% level), and the coefficient of $Treat_i \times post_i$ in Column (2) is −0.051 (significant at the 1% level), suggesting that after controlling for other variables, adopting robo-advising leads to 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, suggesting that the effect size is large on investors' portfolio diversification. The size of robo-advising's education effect on framing bias is medium, with 0.15 standard deviations of the level before adopting robo-advising. In the untabulated results, we find that investors lower their trading frequency after signing up for robo-advising, but the economic magnitude is moderate.

[Insert Table 7 Here]

Table 8 reports results of robo-advising's effect on investor behavioral bias 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 with the non-adopters, robo-advising adopters are less subject to tail return overweight. The changes in extrapolation bias are similar. Investors display less availability bias after adopting robo-advising, and even less bias compared with the non-adopters. Collectively, evidence in this section suggests that investors learn from robo-advising and exhibit less behavioral bias after interacting with the robo-advisor.

However, the economic magnitude of the effect on behavioral biases in fund choices are generally lower than for portfolio management (underdiversification and framing effect), at 5.96% of the standard deviation for availability bias, 1.85% for tail return overweight, and 2.59% for extrapolation bias. Figure 6 summarizes the economic significance of the spillover effect on different behavioral biases. We propose two reasons to explain the discrepancy. First, investors view their BangNiTou portfolios more frequently so they change their minds and behaviors, intentionally or subconsciously, by mimicking the robo-advising portfolio. Second, investors' behavioral biases in fund choices are also related to brokers' marketing strategy that exploit rather than mitigate investors' biases to maximize their own sales, and robo-advising's impact is partly offset by this effect.

[Insert Table 8 Here]

[Insert Figure 6 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 9. We partition the full sample into two subsamples by investor sophistication measured by the pre-adoption behavior pattern examined in each column respectively. The variable of interest is the interaction term of post and low sophistication. For instance, in Column (1), where the effect examined is portfolio concentration, low sophistication is defined to be 1 if the investor's portfolio concentration before adopting BangNiTou is below the sample median, and 0 otherwise. Low sophistication is defined analogously in the other five columns. In Column (1), the coefficient of *Post*Low Sophisticated (1/0)* is significantly negative, suggesting that investors with portfolios with low diversification diversify more after adopting robo-advising. As reported in all six columns of Table 9, we find that except for the framing effect, low-sophistication investors improve more in the other five aspects of investment behaviors, indicating that robo-advising's education effect is greater for investors who are more naive.

[Insert Table 9 Here]

5.2.3 Causality of the education effect

Self-selection bias is the main 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 the unobserved time-invariant difference between adopters and non-adopters, but we still need to address the concern of unobserved time-variant factors. For instance, adopters may join a financial program that simultaneously improves their financial sophistication and promotes the benefit of delegating investment to professional advisors. In that case, the positive effect documented in the PSM sample overstates the impact of robo-advising because the behavioral changes could also be results of the program.

We address this concern by exploring BangNiTou's marketing campaigns. To convert more Alipay users to BangNiTou users, BangNiTou used pop-up advertising to Alipay users from October

2020 through December 2020. All users whose account balance was over 100 RMB had an equal chance of receiving the pop-up ads because Alipay platform randomly selected some users and send them BangNiTou ads. Targeted users could see the ads once they logged into the app during the period. Statistics in Table 10 suggest that the pop-up advertising effectively converted many Alipay users to BangNiTou adopters. In Table 10, we divide all investors in Alipay during October through December 2020 into four groups, with Group A representing investors who had been exposed to the ads and adopted BangNiTou, Group B representing investors who had not been exposed to the ads but adopted BangNiTou, Group C representing investors who had been exposed to the ads but did not adopt BangNiTou, and Group D representing investors who had not been 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 pop-up ads effectively converted many 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 during the three months before and after adoption. After this restriction, as reported in the second row in Table 10, the percentage of BangNiTou subscribers of all investors exposed to the ads is 8.87%, still larger than the percentage for investors unexposed to the ads (6.40%). 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 7. 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 10. 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 10 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. 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:

$$C\hbar g\_Bias_i = a + \beta_1 Treat_i + \gamma control_i + e_i \tag{3}$$

where $C\hbar g\_Bias_i$ 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 as 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 7 and 8. Tables 11 and 12 report results for the PSM sample.[14]

Table 11 reports results for how adopting robo-advising changes investors' portfolio management. The coefficients for *Treat* from Columns (1) – (6) are all significantly negative, suggesting that adopting robo-advising leads to investors having more diversified portfolios and being less subject to framing bias. The significantly negative coefficients of *Treat* in Columns (2), (4), and (6) suggest that our findings survive the identification strategy that uses whether investors are exposed to a BangNiTou advertisement as the instrumental variable. Table 12 reports results for how adopting robo-advising changes investor behavior in fund choices. Consistent with Tables 7 and 8, the coefficients of *Treat* in Columns (1), (3), and (5) are all significantly negative, suggesting that after adopting robo-advising investors exhibit less tail return overweight, less extrapolation bias, and less availability bias. As reported in Columns (2) and (4), the 2SLS results also suggest that investors are less subject to tail return overweight and extrapolation bias. The 2SLS results for availability bias is weaker, with the coefficient of *Treat* in Column (6) being negative but

[14] In the untabulated tables, we also conduct the same tests using the full sample and results are similar.

insignificant. Overall, our finding that adopting robo-advising improves investor sophistication survives the identification strategy in five of six measures of investor behavior in portfolio management and fund choice, alleviating the concern of selection bias. Moreover, the magnitude of the coefficients of *Treat* in the 2SLS regressions are generally three to four times as large as those in the OLS regressions, suggesting that the improvement in financial sophistication is greater for robo-advising adopters that were affected by BangNiTou's advertisement.

[Insert Table 11 Here]

[Insert Table 12 Here]

6. Mechanisms of robo-advising's education effect

This section explores the channels through which robo-advising affects investor decisions and behavior. We propose two channels, namely, repeated and intensified interactions and portfolio models that are specific and easy to follow.

6.1 Repeated interaction intensifies the education effect

Prior literature points out that the forms of financial education that are one-off and about general knowledge have a limited effect on such sophisticated decisions as portfolio management (Duflo & Saez, 2003; Lusardi & Mitchell, 2014). In contrast, BangNiTou provides investors opportunities to repeatedly interact with financial advice through its portfolio reports and service notes. Portfolio reports contain all critical details of the portfolios, including all mutual funds in the portfolio and their respective performance over certain periods, and investors can trace how the portfolio is rebalanced through comparing reports of different quarters. Additionally, investors can access the content of service notes any time by logging in to the app; highlights of important tips are posted on the first page. These features allow BangNiTou to reinforce its education effect through intensified interaction with investors. Therefore, we predict that the education effect is stronger for investors who staying longer on the BangNiTou app.

We include the interaction term of *post* and the length of time on the BangNiTou app in equation (1); the variable of interest captures the cross-sectional variation in investors with different levels of interaction with the robo-advisor. Table 13 reports the results. The significantly negative coefficients in Columns (1), (3), and (4) indicate that investors who stay longer on the BangNiTou app have more diversified portfolios and display less framing bias and tail return overweight. There is no result for extrapolation bias or availability bias. Collectively, we find evidence that the education effect of robo-advising can be reinforced by intensified interaction between the adopters and the robo-advisor.

[Insert Table 13 Here]

We use the time investors spend learning about robo-advising before signing up as another proxy for the intensity of interaction. Investors who spend more time reading information about the robo-advisor are more likely to be affected by robo-advising. Results reported in Table 14 generally support our prediction. The coefficients of the interaction term *post*Subscription time (1/0)* are significantly negative in four out of the six columns. Investors who spend more time learning in BangNiTou have more diversified portfolios and display less framing bias and availability bias.

[Insert Table 14 Here]

6.2 Easy-to-follow models and investor learning

We propose that robo-advising can effectively change investor behavior because it sets models that are easy for investors to follow. Even naive investors can learn from robo-advising by simply mimicking its portfolios and fund choices. Investors can learn about robo-advising portfolios by reading BangNiTou's quarterly portfolio reports; therefore, in this section, we analyze how investors learn from the robo-advisor by comparing investment behaviors between investors who have read the reports and those who have not. Learning behavior is depicted through five aspects in the investor's self-directed investment account: 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 her self-directed portfolio and BangNiTou portfolio, constructed based on measures including a market factor, size factor, evaluation factor, momentum factor, and exposure to industry.

Table 15 depicts the differences in learning behaviors in their self-directed accounts between investors who read BangNiTou portfolio reports and those that do not. Investors who read the report buy more mutual funds that appear in their recent BangNiTou portfolios, more funds increasingly held in BangNiTou portfolios and managed by fund companies appearing in BangNiTou portfolios, sell funds that BangNiTou holds less of, and have an investment style more similar to BangNiTou. Collectively, these findings are consistent with the fact that investors learn from robo-advising by following portfolio models set by BangNiTou. For instance, in the first quarter after adopting BangNiTou, on average, the share of mutual funds appearing in BangNiTou portfolios of investors who have read BangNiTou reports is 1.11%, significantly higher than that for investors who have not read reports (0.92%). The patterns are similar for the second and third quarters.

[Insert Table 15 Here]

To solidify the easy-to-follow argument, we conduct a placebo test by examining the learning effect though service notes. Service notes contain financial knowledge and investment instructions useful to improving investor sophistication, but they are different from portfolio reports; investors need to learn how to apply service notes rather than simply imitating them. In other words, service notes are not as easy to follow as BangNiTou portfolios. If the easy-to-follow feature is important, we would see a discrepancy in the learning effect between reading portfolio reports and service notes. Consistent with our prediction, we find no significant difference in learning behaviors between investors reading service notes and those who do not read them in four of the five aspects (with the exception of investment style), suggesting that investors are more likely to change their behaviors when the learning is easier, especially when mimicking is possible.

7. Conclusion

This study investigates how robo-advising changes personal wealth management based on individual investor account-level data on trades and portfolios by BangNiTou, a Chinese robo-advising platform integrated into the Alipay mobile phone app. Robo-advising has both direct and indirect (spillover) effects on adopters. As the direct effect, we find that robo-advising portfolios show better investment performance as measured by lower volatility and a higher Sharpe ratio. Robo-advising performs better than self-directed portfolios because they not only exploit the benefits of diversification and index investment, but also mitigate behavioral biases in fund choices and portfolio management.

More importantly, robo-advising has significantly positive externality: it improves investor sophistication. After adopting robo-advising, investors' self-directed accounts are more diversified and exhibit fewer behavioral biases in fund choices and portfolio management. Interestingly, the economic magnitude of the reduction on behavioral biases in fund choices is much lower than that in portfolio management. One possible explanation for the disparity is that the fund choice decision is affected not only by investor cognitive bias but also the conflicts of interest between investors and fund sales agencies, that is, human advisors may cater to investors' preference for funds with better recent performance and promote these funds to boost sales.

Furthermore, the spillover effect is more prominent for adopters who interact with the service more actively and who were less rational beforehand. We also find evidence that adopters learn from robo-advising by simply imitating the robo-advisor' s portfolios or strategies. These findings indicate that robo-advising effectively plays a role in educating investors through repeatedly interacting with its adopters and setting investment models that are easy to follow, thereby shedding light on research and practice in financial education.

This study also has important implications for financial inclusion. Naive and lower-income households have limited access to traditional financial advisory services, and neither groups has the knowledge and skills necessary to invest in capital markets by themselves. BangNiTou, the robo-advising app integrated into Alipay—the biggest "super app" in China—is accessible to most households and, together with its low opening balance (less than RMB 1,000), attracts many lower-income and younger investors. We show that even poorer and younger investors can benefit from delegating their investments to the robo-advisor. However, our finding that investors only allocate a small portion in robo-advisor portfolios that have higher Sharpe ratios than their self-directed portfolios emphasize the importance of financial education: naive investors need not only convenient and affordable access to financial advisory services, but knowledge and awareness to leverage this service in household wealth management.

Overall, our paper not only solidifies the fact that robo-advising improves investors' investment performance, but it also provides empirical evidence, based on a large-sample administrative data set, on the effectiveness of robo-advising as a financial education tool that changes financial behaviors of households, especially poorer and younger investors.

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Appendix: Variable Definitions

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.

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.

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.

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 there is individual asset trading 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 characteristics of BangNiTou adopters (before 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 during the twelve months before adoption and then report descriptive statistics of all variables across investors. 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 characteristics of BangNiTou adopters (after adoption)

Table 2 presents descriptive statistics of portfolio characteristics, trading behaviors, and digital footprints of BangNiTou adopters during the eight months after adoption. We first calculate the average characteristics of each variable for each investor during the eight months after adoption and then report descriptive statistics of all variables across investors. 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	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 delegated 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, monthly 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 month *t*. 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 Investment behaviors: self-directed portfolios vs. BangNiTou portfolios

Table 4 compares portfolio characteristics and investment behavioral biases 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. Portfolio characteristics include *index fund ratio*, *equity fund ratio*, *debt fund ratio*, *portfolio concentration*, and *fund correlation*. Investment behavioral biases include *framing bias*, *availability bias*, *extrapolation bias*, and *tail return overweight*. See Appendix A for detailed definitions of variables. The column headed "(3)–(1)" ("(3)–(2)") display the difference in investment behaviors 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)
Index fund ratio	Mean	**0.291**	**0.262**	**0.636**	**0.345**	**0.373**
	SE	0.0010	0.0009	0.0006	0.0013	0.0011
Equity fund ratio	Mean	**0.714**	**0.805**	**0.624**	**-0.089**	**-0.182**
	SE	0.0011	0.0009	0.0010	0.0015	0.0014
Debt fund ratio	Mean	**0.256**	**0.146**	**0.376**	**0.119**	**0.228**
	SE	0.0011	0.0009	0.0010	0.0015	0.0013
Portfolio concentration	Mean	**0.512**	**0.326**	**0.187**	**-0.299**	**-0.110**
	SE	0.0010	0.0009	0.0003	0.0011	0.0008
Fund correlation	Mean	**0.655**	**0.609**	**0.553**	**-0.098**	**-0.051**
	SE	0.0007	0.0006	0.0008	0.0010	0.0009
Framing bias	Mean	**-0.958**	**-1.604**	**-3.075**	**-2.069**	**-1.411**
	SE	0.0048	0.0072	0.0114	0.0110	0.0124
Availability bias	Mean	**0.144**	**0.148**	**0.008**	**-0.132**	**-0.136**
	SE	0.0005	0.0004	0.0001	0.0005	0.0004
Extrapolation bias	Mean	**0.490**	**0.661**	**0.052**	**-0.430**	**-0.602**
	SE	0.0011	0.0011	0.0004	0.0014	0.0014
Tail return overweight	Mean	**0.540**	**0.586**	**0.503**	**-0.036**	**-0.082**
	SE	0.0003	0.0004	0.0003	0.0004	0.0005

Table 5 Investor characteristics and performance improvement through robo-advising

Table 5 explores the relation between investor characteristics and performance improvement through robo-advising. The dependent variable is the average difference of the style-adjusted Sharpe ratio between an investor's BangNiTou portfolio and self-directed portfolio from one month to eight months after adopting the robo-advising. Column (1) displays the results of demographic characteristics. Column (2) displays the results of average portfolio characteristics during the twelve months before adopting robo-advising. Column (3) displays the results of the average investment behavioral biases during the twelve months before adopting robo-advising. Column (4) displays the results of investment behaviors related to robo-advising. Column (5) presents the results when simultaneously including all variables in Columns (1), (2), (3), and (4) in the regression. See Appendix A for detailed definitions of variables. *Subscription strategies* indicate dummy variables of various robo-advising strategies adopted. These strategies vary in the debt and equity fund ratio in the portfolio. *Subscription months* indicates dummy variables for months adopting robo-advising, which ranges from July 2020 to December 2020. *Subscription channels* indicates dummy variables of channels through which investors sign up for BangNiTou. Section 5.2.3 introduces detailed information on subscription channels. The regression coefficients and its robust standard errors are reported. Here, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables: Performance Improvement Through Robo-Advising					
Variables	(1)	(2)	(3)	(4)	(5)
Constant	0.0211***	0.0154***	-0.0213***	0.0068	-0.0353***
	0.0012	0.0047	0.0064	0.0039	0.0095
Top City (1/0)	-0.0005				-0.0013
	0.0013				0.0013
Female (1/0)	0.0006				0.0013
	0.0014				0.0014
Born after 1990 (1/0)	-0.0007				0.003**
	0.0013				0.0014
Log (Total assets)		-0.0001			-0.0022***
		0.0004			0.0006
Equity fund ratio		0.0107***			-0.0082**
		0.0029			0.0033
Index fund ratio		0.024***			0.0381***
		0.0046			0.0048
Portfolio concentration			-0.0264***		-0.0143***
			0.003		0.0031
Framing bias			0.0014***		0.0015***
			0.0005		0.0005
Tail return overweight			0.0934***		0.0971***
			0.0127		0.0127
Extrapolation bias			0.0148***		0.0131***
			0.0026		0.0025
Availability bias			-0.0238***		-0.0076
			0.0073		0.0072

Portfolio turnover			0.0029***		0.0033***
			0.0006		0.0006
Log (BangNiTou asset)				0.0013***	0.0022***
				0.0005	0.0006
BangNiTou asset ratio				-0.047***	-0.0599***
				0.0057	0.0069
Log (1/BangNiTou Turnover)				0.0052**	0.0061***
				0.0023	0.0024
Log (BangNiTou Logins)				0.0031**	0.0018
				0.0013	0.0013
Subscription strategies	N	N	N	Y	Y
Subscription months	N	N	N	Y	Y
Subscription channels	N	N	N	Y	Y
Obs.	74,090	74,090	74,090	74,090	74,090
Adjusted R^2	0	0.0011	0.0045	0.0572	0.0621

Table 6 Analysis of investor characteristics that determine robo-advising adoption

Table 6 presents results for the Probit model of what investor characteristics determine robo-advising adoption. The dependent variable is whether the investor signs up for BangNiTou, and independent variables include average portfolio characteristics and investment behaviors within the 12 months before signing up for the robo-advisor. Column (1) presents the results using the sample that consists of robo-advising adopters and non-adopters obtained from stratified sampling. Column (2) displays the results using the sample that consists of robo-advising adopters and PSM matched non-adopters. The regression 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
Constant	-0.2393***	-0.0348
	0.018	0.030
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
Obs.	879132	148180
Pseudo R^2	0.0452	0.0001

Table 7 Impact of robo-advising on investors' self-directed portfolio management

Table 7 analyzes how robo-advising impacts adopters' self-directed portfolio management. 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 *portfolio concentration*, *fund correlation*, and *framing bias*. Subscript *i* indicates different investors. Subscript *period* equals 1 for observations after the sign-up, and 0 otherwise. *Post* equals 1 for observations after the robo-advisor sign-up, 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 PSM matched non-adopters constructed in Section 4 and the regression equation is as follows:

$$DepVar_{i,period} = a + \beta_1 post_i + \beta_2 Treat_i + \beta_3 Treat_i \times post_i + \gamma control_{i,period} + v_i + e_{i,period.} \quad (2)$$

Treat equals 1 for investors who adopt robo-advising, and 0 otherwise. Other specifications and variables are similar to that of Model (1). Individual investor fixed effects are included in all specifications. The 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*	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Constant	1.3029***	1.2715***	0.8789***	0.885***	-0.4264***	-0.5959***
	0.0101	0.0083	0.0089	0.0072	0.0651	0.0483
Post	-0.0825***	-0.0344***	-0.0608***	-0.0244***	-0.2918***	-0.0934***
	0.0013	0.0012	0.0011	0.0011	0.0074	0.0063
*Treat*Post*		-0.0506***		-0.0367***		-0.2004***
		0.0014		0.0012		0.0078
Log (Total assets)	-0.0686***	-0.0645***	-0.0234***	-0.0231***	-0.1059***	-0.095***
	0.001	0.0008	0.0009	0.0007	0.0058	0.0043
Style-adjusted Sharpe ratio	0.1043***	0.0973***	0.1573***	0.1502***	0.0336	0.015
	0.0061	0.0049	0.0058	0.0048	0.0312	0.0226
Equity fund ratio	-0.2***	-0.191***	0.0772***	0.0777***	-0.5011***	-0.2971***
	0.0038	0.0029	0.0032	0.0025	0.0226	0.0161
Portfolio concentration					1.4668***	1.5026***
					0.0231	0.0172
Framing bias	0.0374***	0.0449***	0.0066***	0.008***		

	0.0006	0.0006	0.0005	0.0004		
Tail return overweight	0.0054***	0.0036***	-0.0455***	-0.0441***	-0.0412***	-0.0246***
	0.001	0.0008	0.001	0.0008	0.0056	0.0041
Extrapolation bias	-0.0295***	-0.0285***	0.0337***	0.032***	0.1099***	0.0732***
	0.0025	0.002	0.0023	0.0018	0.013	0.0091
Availability bias	-0.0804***	-0.0919***	0.0086	-0.008	-0.1157***	-0.1002***
	0.0065	0.0051	0.0057	0.0043	0.0318	0.0217
Portfolio turnover	0.011***	0.0113***	-0.0121***	-0.0127***	-0.0851***	-0.0766***
	0.0007	0.0005	0.0006	0.0005	0.0034	0.0024
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 8 Impact of robo-advising on investors' behavioral biases in self-directed fund choices

Table 8 analyzes how robo-advising impacts adopters' behavioral biases in self-directed 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* indicates different investors. Subscript *period* equals 1 for observations after the sign-up, and 0 otherwise. *Post* equals 1 for observations after the robo-advisor sign-up, 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 PSM matched non-adopters constructed in Section 4, and the regression equation is as follows:

$$DepVar_{i,period} = a + \beta_1 post_i + \beta_2 Treat_i + \beta_3 Treat_i \times post_i + \gamma control_{i,period} + v_i + e_{i,period}. \quad (2)$$

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

	Tail return overweight		*Extrapolation bias*		*Availability bias*	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Constant	0.4635***	0.4805***	0.4495***	0.4598***	0.0652***	0.0792***
	0.0052	0.0044	0.0178	0.015	0.0078	0.0065
Post	0.0351***	0.0443***	0.1534***	0.1556***	-0.0086***	-0.0046***
	0.0006	0.0006	0.002	0.0021	0.0009	0.0009
*Treat*Post*		-0.0069***		-0.0077***		-0.0069***
		0.0007		0.0024		0.0009
Log (Total assets)	0.0027***	0.0016***	0.001	0.0011	0.0057***	0.0052***
	0.0005	0.0004	0.0016	0.0014	0.0007	0.0006
Style-adjusted Sharpe ratio	-0.0465***	-0.0496***	-0.078***	-0.0657***	0.0403***	0.0488***
	0.0029	0.0026	0.0095	0.0081	0.0041	0.0034
Equity fund ratio	0.1279***	0.12***	0.1955***	0.1778***	0.0716***	0.0624***
	0.0017	0.0014	0.0059	0.0048	0.0025	0.0021
Portfolio concentration	-0.0027	-0.0008	-0.1021***	-0.1093***	-0.0427***	-0.0525***
	0.0019	0.0017	0.0066	0.0056	0.0028	0.0024
Framing bias	-0.0011***	-0.0011***	0.0082***	0.0068***	-0.0006	-0.0009***

	0.0003	0.0002	0.0009	0.0008	0.0004	0.0003
Portfolio turnover	0.0052***	0.0048***	0.0142***	0.0171***	0.0167***	0.0175***
	0.0003	0.0003	0.001	0.0009	0.0005	0.0004
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 9 Adopters' sophistication and the spillover effect

Table 9 investigates whether the spillover effect of robo-advising varies with adopters' sophistication. The dependent variables are *portfolio concentration*, *fund correlation*, *framing bias*, *availability bias*, *extrapolation bias*, and *tail return overweight*. Adopters' sophistication is measured depending on investment behaviors we investigate. For example, in the column headed "*Portfolio concentration,*" Sophisticated (1/0) is defined as 1 if an adopter's average portfolio concentration during the twelve months before signing up for robo-advising is lower than the sample median, and 0 otherwise. We then add an interaction item, *Post*Sophisticated (1/0)*, into Model (1). The 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*
Constant	1.1263***	0.7716***	-0.4308***	0.4563***	0.3639***	0.0498***
	0.0093	0.0077	0.0651	0.0049	0.0147	0.0067
Post	0.0061***	0.0514***	-0.3344***	0.062***	0.3457***	0.0705***
	0.0011	0.0013	0.0097	0.0007	0.0022	0.0009
Post*Low Sophisticated (1/0)	**-0.2129*** **	**-0.1995*** **	**0.1042*** **	**-0.0514*** **	**-0.3752*** **	**-0.1498*** **
	0.0015	**0.0014**	**0.0107**	**0.0007**	**0.0023**	**0.001**
Log (Total assets)	-0.0519***	-0.0137***	-0.1081***	0.0034***	0.0086***	0.0061***
	0.0009	0.0008	0.0059	0.0004	0.0013	0.0006
Style-adjusted Sharpe ratio	0.0767***	0.0728***	0.0349	-0.05***	-0.1185***	-0.0024
	0.0056	0.005	0.0313	0.0029	0.008	0.0035
Equity fund ratio	-0.1863***	0.0587***	-0.4877***	0.1188***	0.1786***	0.0672***
	0.0033	0.0028	0.0226	0.0016	0.0049	0.0021
Portfolio concentration			1.5227***	0.0051***	-0.0704***	-0.0174***
			0.0239	0.0018	0.0055	0.0024
Framing bias	0.0392***	0.007***		-0.0015***	0.006***	-0.0019***
	0.0005	0.0004		0.0002	0.0007	0.0003
Tail return overweight	-0.0014	-0.0124***	-0.044***			
	0.0009	0.0009	0.0056			
Extrapolation bias	-0.015***	0.0299***	0.1059***			
	0.0023	0.002	0.013			
Availability bias	-0.0465***	0.0228***	-0.1274***			

	0.0061	0.005	0.0318			
Portfolio turnover	0.008***	-0.0077***	-0.0869***	0.0041***	0.0104***	0.0136***
	0.0006	0.0005	0.0035	0.0003	0.0009	0.0005
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 10 Statistics on the subsample of investors for identification

In Table 10, we divide sample investors in Alipay during October through December 2020 into four groups, with Group A representing investors who had been exposed to the ads and adopted BangNiTou, Group B representing investors who had not been exposed to the ads but adopted BangNiTou, Group C representing investors who had been exposed to the ads but did not adopt BangNiTou, and Group D representing investors who had not been exposed to the ads and did not adopt BangNitou. We calculate the percentage of BangNiTou subscribers of investors exposed and unexposed to the robo-advisor advertisement, respectively.

Sample selection	Group				Percent of BNT subscriber	
	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 11 The IV results of the spillover effect on self-directed portfolio management

Table 11 estimates the impact of robo-advising on adopters' self-directed portfolio management 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 investment characteristics after signing up for robo-advising. The dimensions 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 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.

	Portfolio concentration		*Fund correlation*		*Framing bias*	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.0874***	-0.2795***	0.0938***	0.0881***	-0.1602***	-0.6554***
	0.0021	0.0106	0.0088	0.0218	0.0712	0.1836
Treat	**-0.0945*****	**-0.4146*****	**-0.0509*****	**-0.1367*****	**-0.4116*****	**-2.0888*****
	0.0029	**0.0595**	**0.0024**	**0.0412**	**0.0171**	**0.3345**
Log (Total assets)	-0.0113***	-0.0110***	-0.0033***	-0.0033***	-0.008	-0.009
	0.009	0.0011	0.0008	0.0008	0.0054	0.0064
Style-adjusted Sharpe ratio	0.1562***	0.1546***	0.2244***	0.2243***	-0.122	0.1153
	0.0134	0.0148	0.0116	0. 0116	0.0657	0.0779
Equity fund ratio	-0.1291***	-0.1343***	0.0325***	0.0327***	-0.1947***	0.2248***
	0.0068	0.0084	0.0053	0.0053	0.042	0.0496
Portfolio concentration					-0.0948***	0.0883
					0.0393	0.0459
Framing bias	0.0308***	0.0308***	-0.0081***	-0.0081***		
	0.0011	0.0014	0.0008	0.0008		
Tail return overweight	0.0095***	0.013***	-0.0565***	-0.0566***	0.0504***	0.0689***
	0.0024	0.0028	0.0019	0.0020	0.0119	0.0146

Extrapolation bias	-0.0256***	-0.0168**	0.0092	-0.0089	-0.1155***	0.069
	0.0061	0.0072	0.005	0.0051	0.0306	0.0377
Availability bias	-0.0507***	-0.0424**	0.119***	-0.1187***	-0.1403**	-0.0976
	0.0153	0.0173	0.0124	0.0124	0.0716	0.087
Portfolio turnover	0.0045***	0.005***	-0.0078***	-0.0078***	-0.0198***	-0.0224***
	0.0013	0.0015	0.0011	0.0011	0.0066	0.0076

Table 12 The IV results of the spillover effect on investors' behavioral biases in self-directed fund choices

Table 12 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)
Constant	0. 699***	0.8084***	0.337***	0.3222***	0.0569***	0.0295
	0.0419	0.0947	0.0201	0.0441	0.0085	0.0187
Treat	**-0.0055*** **	**-0.0171*** **	**-0.0087** **	**-0.0194** **	**-0.0072*** **	**-0.0286**
	0.0013	**0.0561**	**0.0046**	**0.087**	**0.0019**	**0.0331**
Log (Total assets)	-0.0049	-0.0048	-0.0122***	-0.0122***	-0.0029***	-0.0029***
	0.0033	0.0033	0.0016	0.0016	0.0007	0.0007
Style-adjusted Sharpe ratio	-0.9155***	-0.9184***	-0.0525***	-0.0521***	-0.0391***	-0.0398***
	0.0514	0.0519	0.0195	0.0195	0.0083	0.0084
Equity fund ratio	1.5166***	1.5147***	-0.2176***	-0.2178***	-0.0516***	-0.0521***
	0.0192	0.0194	0.0097	0.0098	0.0041	0.0042
Portfolio concentration	0.0484	0.0477	0.0966***	0.0965***	0.0491***	0.0489***
	0.0257	0.026	0.0124	0.0124	0.0051	0.0052
Framing bias	0.0232***	0.0233***	0.0024	0.0024	0.0001	0.0001
	0.0037	0.0037	0.0018	0.0018	0.0007	0.0007
Portfolio turnover	0.0298***	0.0295***	-0.0215***	-0.0216***	-0.0148***	-0.0149***
	0.0042	0.0043	0.0019	0.0019	0.001	0.001

Table 13 Interaction intensity and the spillover effect: evidence from *BangNiTou Stay*

Table 13 explores how the intensity of investors' interaction with robo-advising influences the spillover effect. In this table, the interaction intensity is proxied by the monthly average length of time that an investor spends on the BangNiTou app. We estimate the effect by adding an interaction item, *Post*BangNiTou stay (1/0)*, into Model (1). *BangNiTou stay (1/0)* equals 1 if an adopter's monthly average *BangNiTou stay* is larger than the sample median, and 0 otherwise. 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. 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*
Constant	1.3224***	0.8837***	-0.3819***	-0.2172***	0.448***	0.0644***
	0.0103	0.009	0.0741	0.0433	0.018	0.0076
Post	-0.0827***	-0.0616***	-0.2298***	-0.3691***	0.1525***	-0.0083***
	0.0014	0.0013	0.0096	0.0056	0.0023	0.0009
Post*BangNiTou stay (1/0)	**-0.0039****	**0.0013**	**-0.2059*****	**-0.0222*****	**0.0023**	**-0.0011**
	0.0017	**0.0015**	**0.0115**	**0.0067**	**0.0027**	**0.0011**
Log (Total assets)	-0.0709***	-0.024***	-0.1111***	0.0565***	0.001	0.0059***
	0.001	0.0009	0.0067	0.0039	0.0016	0.0007
Style-adjusted Sharpe ratio	0.1066***	0.1586***	0.0267	0.6571***	-0.0827***	0.0377***
	0.0059	0.0056	0.0336	0.0291	0.0092	0.0038
Equity fund ratio	-0.2047***	0.0771***	-0.5462***	-0.5671***	0.1959***	0.0723***
	0.0038	0.0032	0.0252	0.0134	0.0059	0.0024
Portfolio concentration			1.473***	0.1298***	-0.0999***	-0.044***
			0.0255	0.0164	0.0065	0.0027
Framing bias	0.0302***	0.005***		-0.0182***	0.0075***	-0.0004
	0.0006	0.0004		0.002	0.0008	0.0003
Tail return overweight	0.0049***	-0.0447***	-0.0457***			
	0.001	0.0009	0.0061			
Extrapolation bias	-0.0286***	0.0342***	0.1259***			
	0.0025	0.0023	0.0142			
Availability bias	-0.0903***	0.0055	-0.1242***			

	0.0066	0.0058	0.0361			
Portfolio turnover	0.0102***	-0.0117***	-0.0893***	-0.0134***	0.0138***	0.0152***
	0.0007	0.0006	0.0037	0.0026	0.001	0.0005
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 14 Interaction intensity and the spillover effect: evidence from time spent on signing up for robo-advising

Table 14 explores how the intensity of investors' interaction with robo-advising influence the spillover effect. In this table, the interaction intensity is proxied by the length of time that an investor spent on singing up for BangNiTou (*Subscription time*). We estimate the effect by adding an interaction item, *Post* Subscription time (1/0)*, into Model (1). *Subscription time (1/0)* equals 1 if an adopter's *Subscription time* is larger than the sample median, and 0 otherwise. The dependent variables are *portfolio concentration*, *fund correlation*, *framing bias*, *availability bias*, *extrapolation bias*, and *tail return overweight*, respectively. The 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*
Constant	1.321***	0.8851***	-0.3266***	-0.2099***	0.4458***	0.0634***
	0.0103	0.009	0.0741	0.0433	0.018	0.0076
Post	-0.08***	-0.0639***	-0.2696***	-0.3757***	0.1556***	-0.0061***
	0.0014	0.0013	0.0098	0.0057	0.0023	0.0009
Post* Subscription time (1/0)	**-0.0098*** **	**0.0061*** **	**-0.1158*** **	**-0.0074**	**-0.0046**	**-0.0058*** **
	0.0016	**0.0015**	**0.0115**	**0.0067**	**0.0027**	**0.0011**
Log (Total assets)	-0.0707***	-0.0241***	-0.1166***	0.0558***	0.0013	0.006***
	0.001	0.0009	0.0067	0.0039	0.0016	0.0007
Style-adjusted Sharpe ratio	0.1065***	0.1587***	0.0319	0.6578***	-0.0829***	0.0376***
	0.0059	0.0056	0.0336	0.0291	0.0092	0.0038
Equity fund ratio	-0.2045***	0.077***	-0.55***	-0.5675***	0.196***	0.0724***
	0.0038	0.0032	0.0253	0.0134	0.0059	0.0024
Portfolio concentration			1.4756***	0.1299***	-0.1001***	-0.0443***
			0.0255	0.0164	0.0065	0.0027
Framing bias	0.0301***	0.005***		-0.0178***	0.0074***	-0.0005
	0.0006	0.0004		0.002	0.0007	0.0003
Tail return overweight	0.0049***	-0.0447***	-0.0449***			
	0.001	0.0009	0.0061			
Extrapolation bias	-0.0286***	0.0343***	0.1252***			
	0.0025	0.0023	0.0142			
Availability bias	-0.0908***	0.0058	-0.129***			

	0.0066	0.0058	0.0361			
Portfolio turnover	0.0102***	-0.0116***	-0.0891***	-0.0134***	0.0137***	0.0152***
	0.0007	0.0006	0.0037	0.0026	0.001	0.0005
Investor FE	Y	Y	Y	Y	Y	Y
Obs.	148180	148180	148180	148180	148180	148180
Adjusted R^2	0.4814	0.1335	0.2117	0.1774	0.2093	0.0456

Table 15 Evidence on adopters' mimicking investment behaviors of robo-advising

Table 15 examines whether adopters mimic investment behaviors of robo-advising in their self-directed accounts. We compare the mimicking behaviors within three quarters after signing up for BangNiTou between adopters that have read BangNiTou portfolio reports and those that have not. Mimicking behaviors are depicted from five aspects: 1) the percentage of the subscription to mutual funds that appear in recent BangNiTou portfolios (Panel A); 2) the percentage of the subscription to mutual funds increasingly held by recent BangNiTou portfolios (Panel B); 3) the percentage of the redemption of mutual funds reduced by recent BangNiTou portfolios (Panel C); 4) the percentage of the subscription of mutual funds managed by fund companies appearing in recent BangNiTou portfolios (Panel D); 5) the distance in investment style between investors' self-directed portfolios and their BangNiTou portfolios (Panel E). The investment style of a portfolio is a composite index constructed based on the portfolio's factor exposures calculated at the end of a quarter including exposures to a market factor, size factor, valuation factor, momentum factor and the industry index. We also report the difference of mimicking behaviors between adopters who have read BangNiTou portfolio reports and those who have not 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

Figure 1 Overview of BangNiTou app

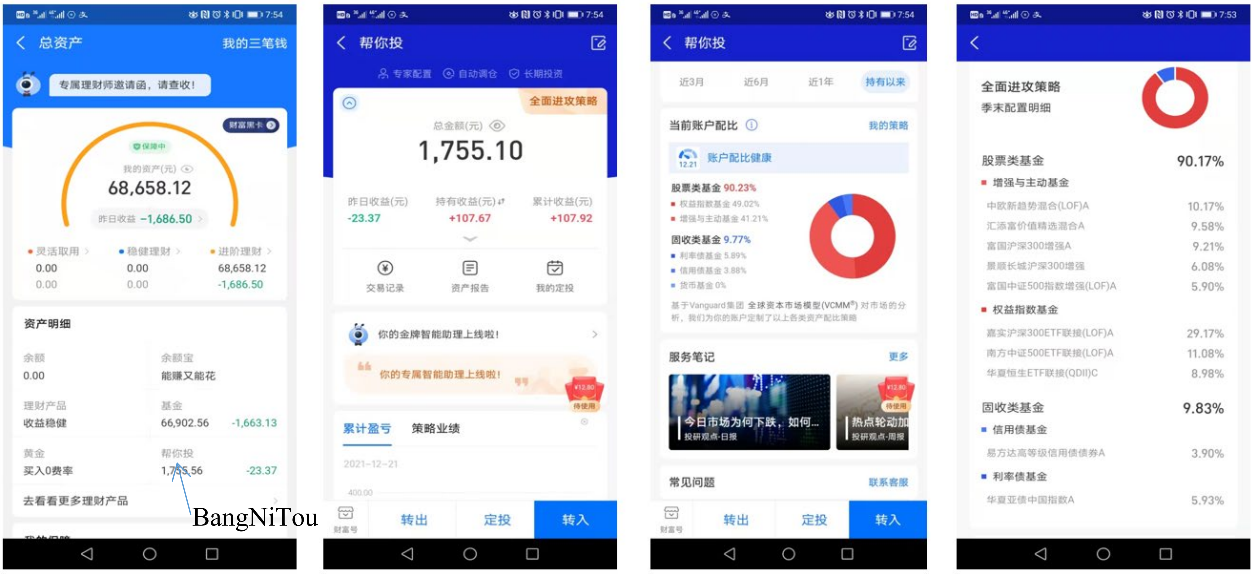


Figure 1 shows screenshots of the BangNiTou app. The first screenshot on the left is the overview of the Alipay investor’s investment portfolio including money market funds, mutual funds, gold, and investments delegated to BangNiTou. The investor can check the total amount of her investment and daily 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, cumulative return, trading records, and quarterly investment reports. The third screenshot from the left presents the BangNiTou account allocation in equity funds and fixed income funds, and the fourth screenshot presents even more detailed portfolio information, for examples, the specific funds held by the investor’s BangNiTou account.

Figure 2 Overview of service notes on BangNiTou App

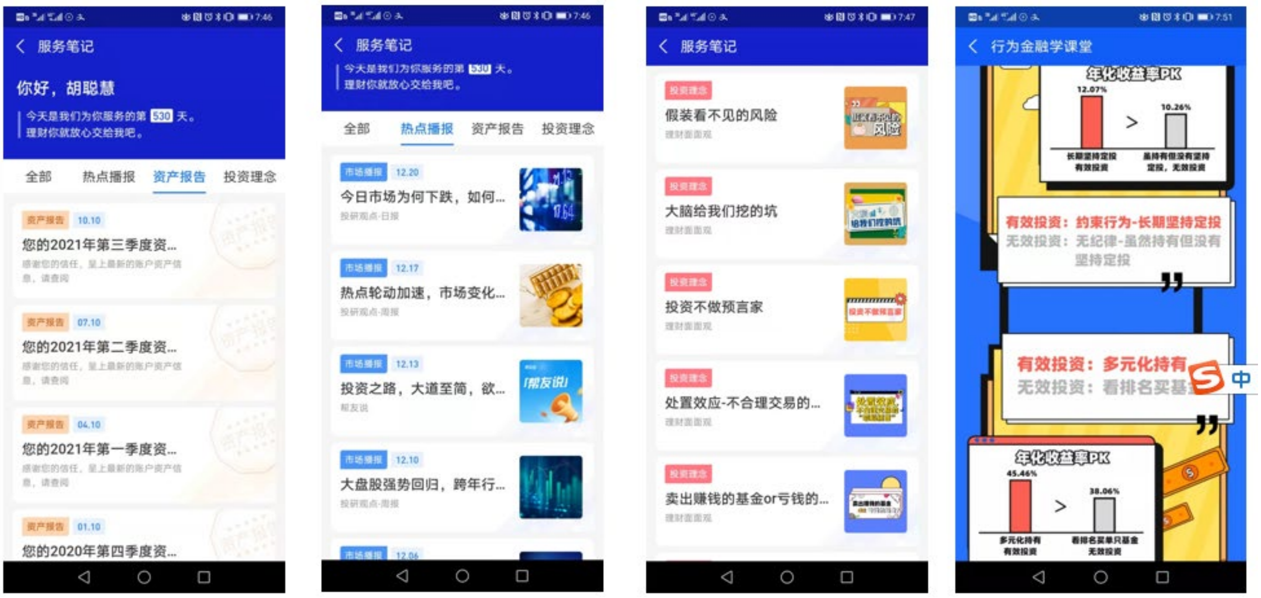
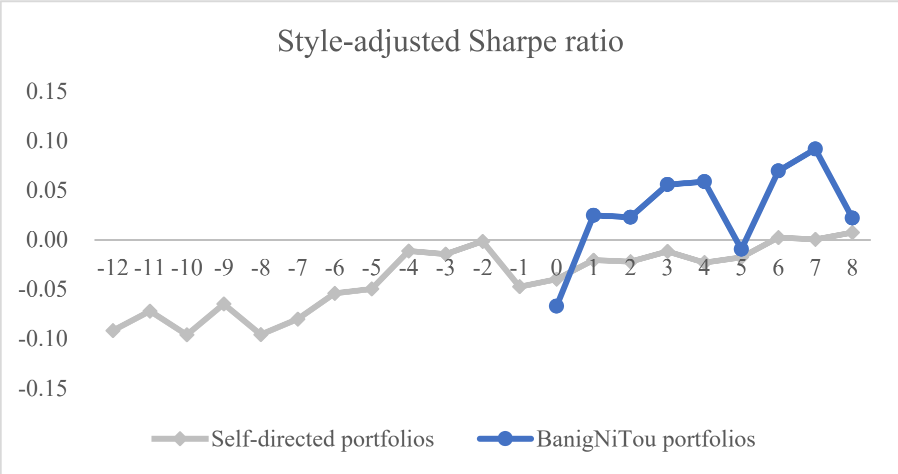


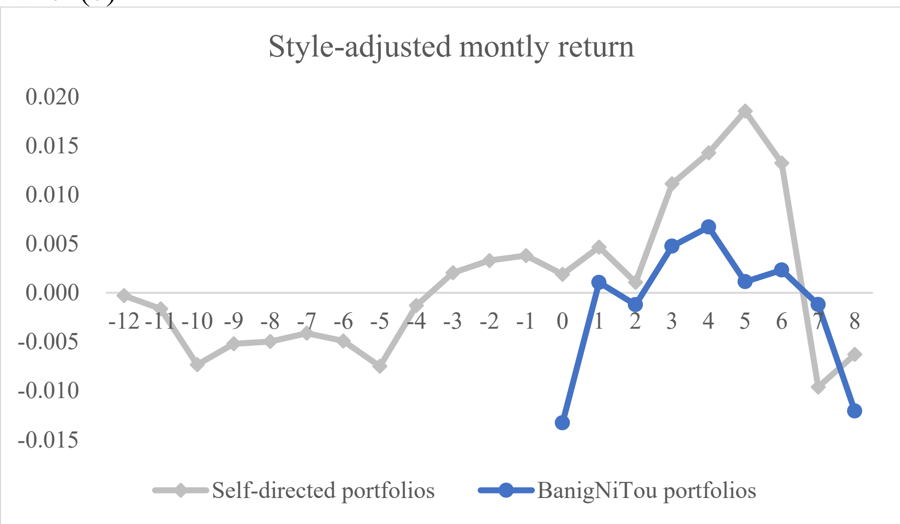
Figure 2 presents screenshots of service notes in the BangNiTou app. The first screenshot on the left shows the quarterly portfolio reports pertaining to the specific investor. The second screenshot from the left contains articles aiming to help investors understand market fluctuations and manage emotions. The third screenshot contains articles about investment principles, for example, investment risks ignored, the traps set by our cognition, and tips on how to overcome behavioral biases. The fourth screenshot contains a learning center regarding behavioral finance, including topics such as failing to discipline oneself and relying on recent past return rankings when buying mutual funds.

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

Panel (a)



Panel (b)



Panel (c)

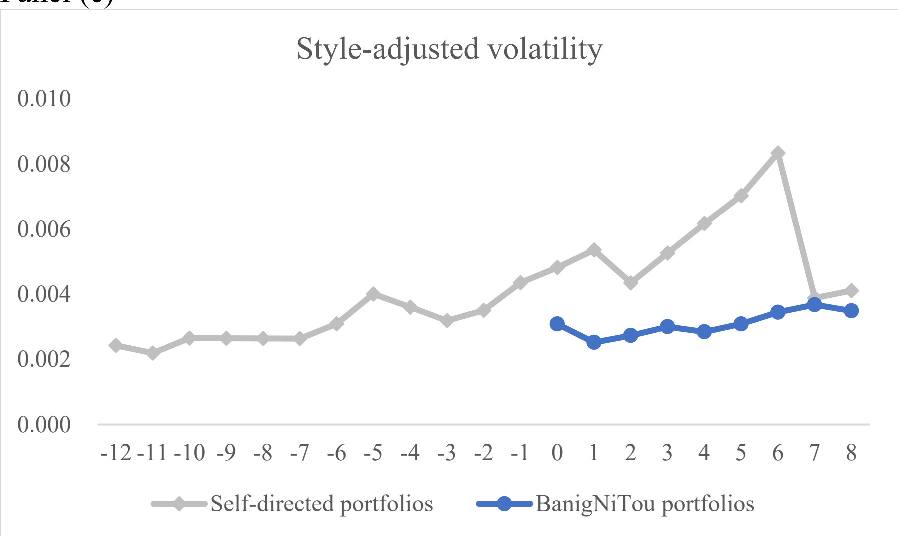
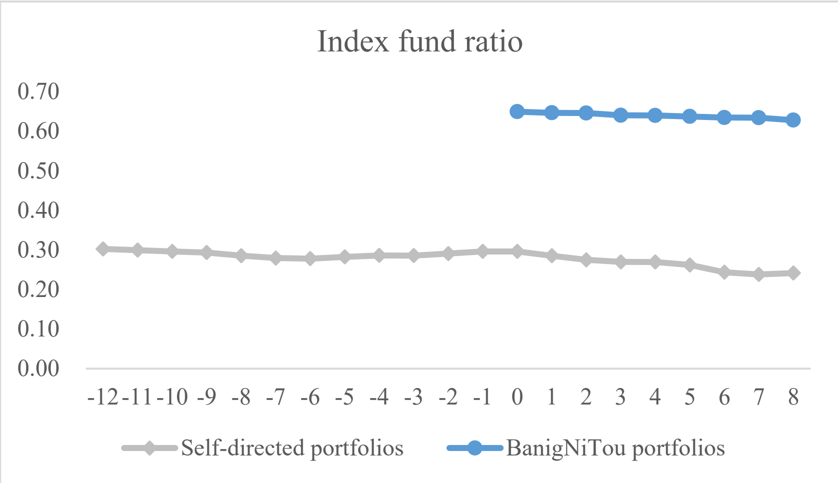


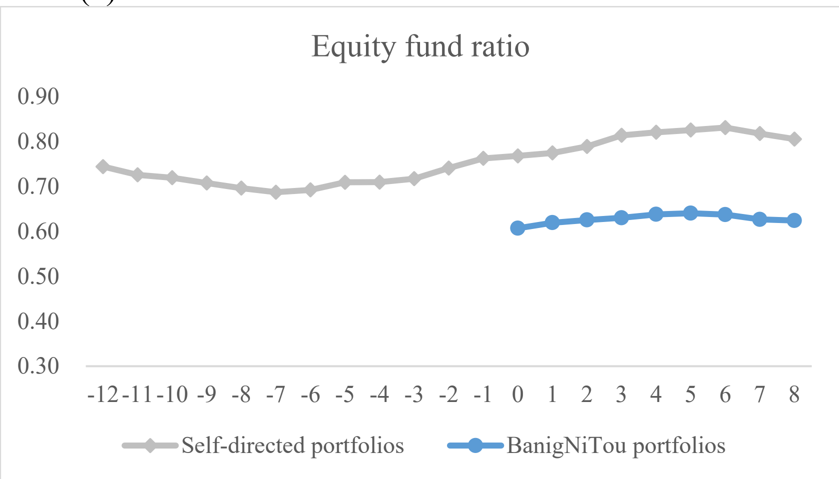
Figure 3 plots the style-adjusted investment performance for investors' BangNiTou portfolios versus their self-directed portfolios from twelve months before to eight months after adopting the robo-advisor. Investment performance is measured by the style-adjusted Sharpe ratio (Panel (a), style-adjusted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

Figure 4 Portfolio characteristics: self-directed portfolios vs. BangNiTou portfolios

Panel (a)



Panel (b)



Panel (c)

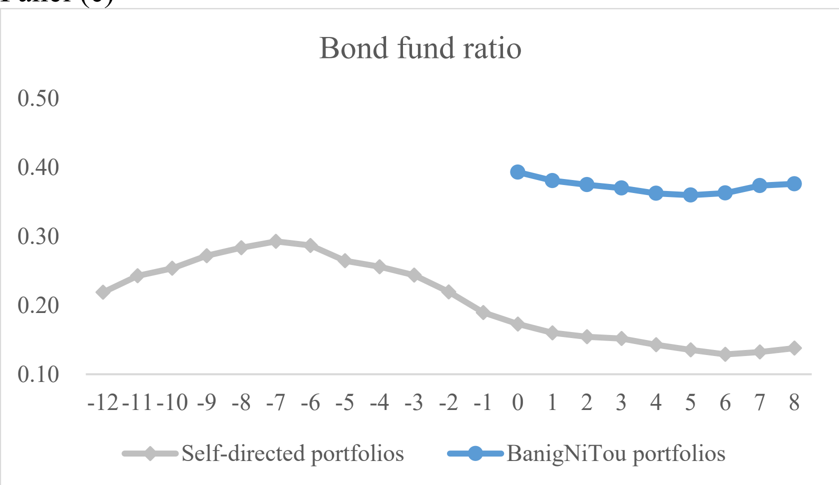


Figure 4 plots portfolio characteristics for investors' BangNiTou portfolios and their self-directed portfolios from twelve months before to eight months after adopting the robo-advisor. Portfolio characteristics include index fund ratio (Panel (a)), debt fund ratio (Panel (b)), and equity fund ratio (Panel (c)).

Figure 5 Investment behavioral biases: self-directed portfolios vs. BangNiTou Portfolios

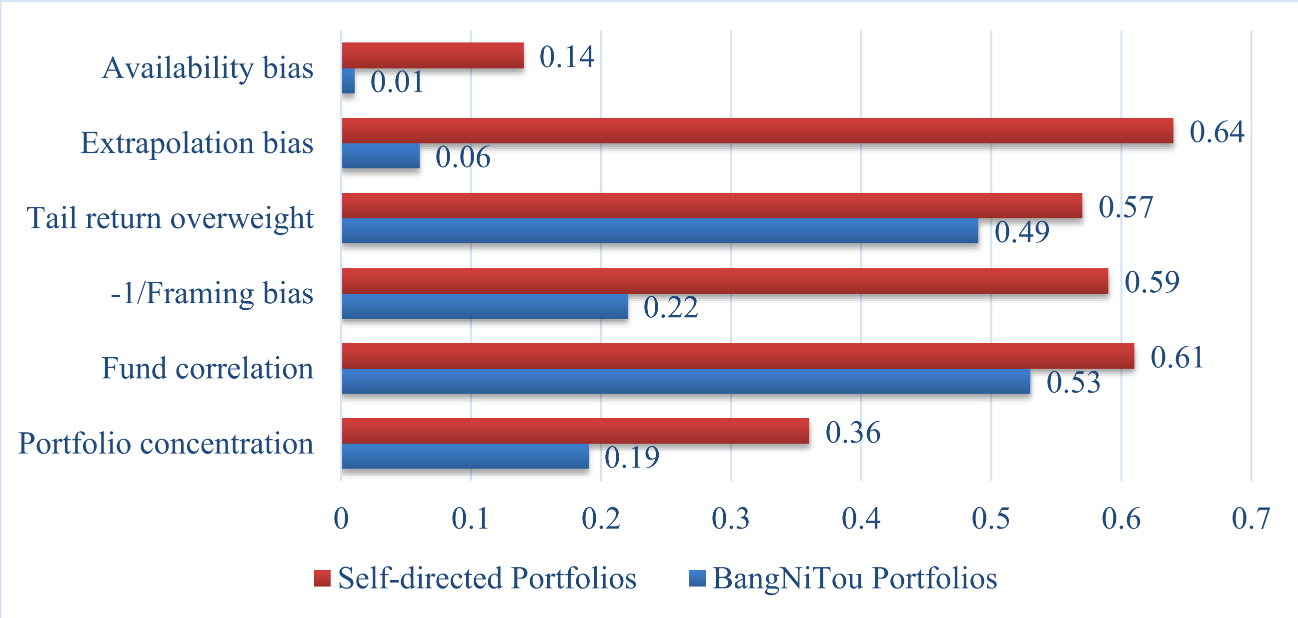


Figure 5 compares the average investment behavioral biases for investors' BangNiTou portfolios and their self-directed portfolios from one month to eight months after adopting the robo-advisor.

Figure 6 The economic significance of spillover effects

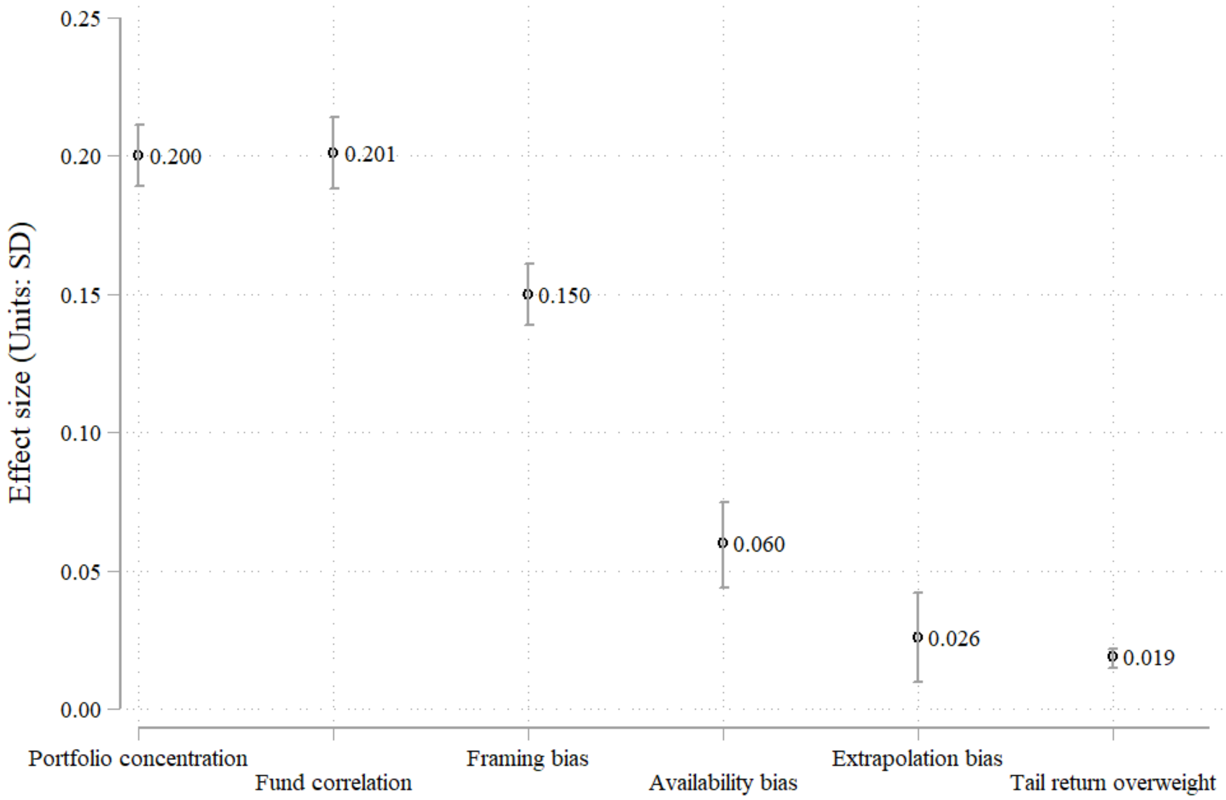


Figure 6 compares the economic significance of the spillover effect on different behavioral biases. For each behavioral bias, the effect size is defined to be the estimated coefficient using Model (2) in Table 7 or Table 8 divided by the sample standard deviation of the behavioral bias in our sample.