Beyond Performance: the Financial Education Role of Robo-advising

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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 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 sophistication. Investors have more diversified portfolios and exhibit fewer behavioral biases in portfolio management and fund choice in their self-directed accounts after adopting robo-advising. The spillover effect is more prominent for adopters that interact with the service more actively and that used to be less rational beforehand. We also find 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. 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.

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

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Abstract

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1. Introduction

Households are supposed to participate in risky asset investment for considerable risk premium, but many of them lack financial knowledge and skills. Therefore, they can delegate their investment to financial advisory. Traditionally, financial advisory hire human advisors to serve their clients and thus are expensive to most households. Only the wealthy households have access to traditional financial advisory. Besides, it is subject to 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 under-performance (Foerster et al., 2017; Linnainmaa et al., 2021).

Robo-advising, which has been rising 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 existing in human advisory[1]. Using proprietary data from BangNiTou (meaning "help you invest" in Chinese), the largest Chinese robo-advisor and the joint venture of Vanguard and Ant Group, we examine whether robo-advising brings its adopters better investment performance as well as making these adopters 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 the adoption. This advantage facilitates us to examine whether individual investors' interaction with robo-advising improves their financial sophistication and change their investment behaviors. In other words, we can investigate whether robo-advising plays a role of financial education. Financial education literature emphasizes the

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

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. (2021) support 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 extant research generally relies on self-reported survey data.[2] 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 it empirically. Additionally, different from extant financial education studies that are more about household saving behaviors, we analyze the effectiveness of financial education on how households participate in risky asset investment, and more specifically, their portfolio management and fund choice.

Second, although robo-advising lowers the advisory fees and are accessible to more households, most robo-advising adopters in prior studies are still wealthy investors, so it is unclear to what extent their findings can be generalizable to poorer and less sophisticated investors[3]. By contrast, the majority of BangNiTou subscribers are younger and less wealthy investors. BangNiTou is integrated into Alipay, initially the world's largest digital payment platform penetrating into most households in China and now the one-stop "super app" that covers almost all demands one can possibly have in everyday life, ranging from ride-sharing to utility bill payment and to mutual fund investment.[4] The entry barrier to sign up for BangNiTou is much lower than all the robo-advisors studied in prior

[2] Kaiser et al.(2021) point our that "few studies can link their experiments to administrative data, so the usual caveats of having to rely on self-reported survey data also apply to these studies. Future research should aim to collect longer-run administrative data".
[3] 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.
[4] Alipay claims to have more than 1 billion users globally. These users can have access to BangNiTou simply by several clicks of the app.

literature.[5] As a result, BangNiTou has a much broader client base and significantly higher portion of poor and young investors[6]. According to Campbell (2006), poorer and less educated households are more likely to make mistakes in investment, such as under-diversification 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 enables us to explore whether robo-advising can improve performance for poor and less sophisticated investors. It also fits the focus of financial education on younger and smaller investors, who are supposed to be less equipped to invest in risky asset and thus need financial education more.

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 specific about how to allocate their assets. Second, the adopters tend to frequently log in their accounts in BangNiTou to check the portfolio performance, which updates on the daily basis, 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 that signed up for BangNiTou during July 2020 through December 2020. Since these adopters invest in BangNiTou through their Alipay account, where we can obtain data on their trades and positions for both BangNiTou accounts and their self-directed accounts, including their investment in mutual funds, money market funds (MMFs), wealth management products (WMPs) and cash, as well as their digital footprints on BangNiTou App. The sample period is July 2019 through March 2021. In

[5] The minimum investment for the subscription of BangNiTou is merely RMB 1,000 (about $150). The annual rate of advisory fee is 0.5% or below (varying with specific strategies), charged on daily basis.

[6] The mean/median of asset for subscribers of BangNiTou is only RMB 67,665/24,272 (about $3,800). 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) of investor age is 29 (30.84) year old.

the analysis of whether robo-advising improves investor sophistication, we use stratified sampling and 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 self-directed accounts. Investment performance is measured by style-adjusted measures including portfolio return, volatility and Sharpe Ratio. Portfolios managed by BangNiTou have lower style-adjusted volatility and higher style-adjusted Sharpe Ratio than investors' self-directed portfolios before they adopt the robo-advisor, consistent with the finding in Rossi & Utkus (2021). Both studies suggest that robo-advising improves investor performance mainly through lowering portfolio volatility. Different from Rossi & Utkus (2021), we further document that BangNiTou portfolios perform better than investor self-directed portfolios of 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.

We examine the channels through which robo-advising improves investment performance. The share of index fund doubles to 60% in BangNiTou portfolios, suggesting that robo-advising directs investors to invest more in index fund. BangNiTou portfolios are more diversified in fund holdings, measured by lower concentration (Herfindal Index) of mutual funds in the portfolio and lower return correlation for mutual funds in the portfolio. Besides, the equity-to-bond ratio of BangNiTou portfolios fluctuates over time less than that of self-directed portfolios, suggesting that robo-advising implements the prescribed strategies and is less affected by the market sentiment.

An important channel through which robo-advising improves investor performance is eliminating behavioral biases in fund choice and portfolio management. Specifically, BangNiTou portfolios display less framing bias, availability bias, extrapolation bias and tail return overweight than investor 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 with non-adopters after the adoption. In all specifications, individual investor fixed effect is included to control for time-invariant and unknown investor characteristics. After adopting BangNiTou, investors' self-directed portfolios get more diversified, measured by lower concentration (Herfindal index) and lower return correlation of funds in the portfolio. BangNiTou adopters also become less affected by framing bias and availability bias after the adoption than non-adopters. The economic magnitudes of the changes are significant for portfolio diversification and framing bias, equivalent to 15%-20% of the standard deviation before signing up BangNiTou. The tail return overweight and extrapolation bias increases after adopting BangNiTou, but the change is significantly lower than non-adopters. Collectively, we find evidence that adopting robo-advising makes investors more sophisticated and less subject to behavioral biases.

Results discussed above cannot control for time-variant unobserved variables. For example, it is possible that robo-advising adopters may take from elsewhere financial education program, which improves their financial literacy and meanwhile promotes investment principles similar with what robo-advising advocates right before signing up BangNiTou. We use BangNiTou's promotion campaign, which advertises to potential investors in the Alipay app and offers them subscription coupons, as our identification strategy to address the concern of unobserved omitted variable. We argue that investors signing up during the campaign are attracted by the promotion of coupons rather than recognizing the benefits of adopting robo-advising for wealth management. We find that investors adopting robo-advising during the promotion campaign take more diversified portfolios and displays fewer behavioral biases in their self-directed portfolios.

Finally, we examine the mechanisms through which BangNiTou improves investors' financial sophistication. Using data on investors' interaction with BangNiTou app, we find that the education

effect is significantly more prominent for investors that stay longer with BangNiTou app and thus are more intensely affected by robo-advising. Investors may spend time in browsing their portfolio performance as well as reading materials posted in the app that contain financial knowledge and investment skills, such as tips on how to diversify one's portfolio or 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 decision.

We also find evidence that robo-advising changes investor behavior through lower difficulty of learning. Investors that 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 with that of their robo-advising portfolios. Our findings suggest that lower difficulty of learning for small investors, such as the easy-to-follow investment portfolios, can effectively change investor behaviors.

2. Related literature and contribution of this study

2.1 Fintech and robo-advising

As fintech emerges as an important player in financial sector and grows sharply over the last decade, academic research in fintech increases accordingly. Goldstein et al. (2019) discuss the impact of fintech rising on household finance and financial institutions from the macroeconomic perspective. Carlin et al. (2017) find that the introduction of a smartphone application for personal financial management changes use of consumer credit and improves financial fitness. Using administrative and survey data from Kenya, Suri et al. (2021) find that the spread of digital loan improves household resilience. Chen et al. (2021) use a RDD research design and show a causal relation between the 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 platform, specifically, the

penetration of Alipay in Chinese daily life, accumulate individuals' trust in fintech firms and thus encourage more risk-taking in household finance. This study relies on instrument variables such as the distance between the Alipay users' residence and Hangzhou, the city Alibaba's headquarter locates in, for identification. It does not explore individual-level mutual fund investment behavior.

Research on robo-advising, the main manifestation of fintech in financial advisory, is still rare. D'Acunto et al. (2019), the first study on robo-advising, investigate how the introduction of an automated stock portfolio optimizer changes investors' portfolio choice and trade decision. They find 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, trend chasing and rank effect. They introduce the notion that robo-advising can perform a financial educational purpose by visualizing the comparison between the position of optimal portfolio and investors' current portfolio, but they have not explored how the education role is actually played.

The robo-advisor in D'Acunto et al. (2019) offers investors portfolio advice and investors can decide to follow the advice or not. Bianchi & 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-advising achieve better investment performance. Different from the two studies, the robo-advisor in Rossi & Utkus (2021) is Vanguard's Personal Advisor Service (PAS), to which investors fully delegate their asset management once they sign up for the service. As the world's largest robo-advisor, PAS automatically allocates asset and rebalance portfolios following algorithms designed and coded by its experts, and human advisors only play a role of explaining the plan to investors before signing-up. PAS manages portfolios including stocks, mutual fund, bond and cash. PAS fully diversifies investors' portfolios, decreases stock holdings and invests more into index fund that has lower management fee, invests internationally and decreases local exposure, increases the share of risky assets including equity and bond holdings, and decreases cash

holdings. As a result, PAS significantly improves investment performance measured by abnormal Sharpe Ratio. Additionally, the improvement in investment performance is significantly larger for those analysts with low share of risky asset, lack of investment experience, with low mutual fund holdings and low index fund holdings. BangNiTou is a robo-advising tool similar with Vanguard PAS except that it has lower entry barrier for subscribers and thus can be accessible for a much wider range of households, especially the low-class ones.[7] As a result, we also find that the portfolios managed by BangNiTou perform better with higher Sharpe Ratio and lower volatility, are more diversified and invest more in index fund.

Our study differs from extant research in several ways. First, the access to individual account-level data on investors' self-directed portfolios both before and after adopting BangNiTou facilitates 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 actually get more sophisticated after adopting robo-advising and the improvement is more significant for investors that ex ante are more naive and interact more with robo-advising. Second, we can examine how robo-advising benefits small investors. Due to the fact that 80-90% of PAS users are clients of Vanguard traditional financial advisory and its minimum investment is set to be $50,000, the majority of PAS robo-advising adopters are not small investors[8]. Reher & Sokolinski (2021) find that lowering the minimum investment of robo-advisors induce more middle-class households to participate in the advisory service and their investment performance improves thereafter, but lower-class households are not affected by the scheme since they are still excluded from financial advisory service overall. In contrast, BangNiTou app is integrated into Alipay app that has penetrated to roughly one billion users, and its entry barrier is only RMB 800 to 1,000, so most

[7] Robo-advisors examined in prior studies may vary in service details. The robo-advisor in D'Acunto et al. (2019) is a stock portfolio optimizer, while the robo-advisors in others manage assets including stocks, equity and bond funds, and cash holdings. The robo-advisor in D'Acunto et al. (2019) and Bianchi & Brière (2021) offers investors portfolio advice and leave investors to decide to follow or ignore the advice, while the robo-advisors in Rossi & Utkus (2021) and Reher & 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.

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

users of BangNiTou app are small investors that are regarded as of worse financial literacy. This feature facilitates us to examine whether and how robo-advising can be beneficial to small investors that have little access to traditional financial advisory service. This has important implication on how fintech promotes financial inclusion. Third, prior studies such as Rossi & Utkus (2021) have to construct the control sample of non-adopters to illustrate how robo-advising improves investors' portfolio performance to control for the observed difference between the robo-advising adopters and non-adopters, but since we can directly observe both the adopters' account holdings in BangNiTou and holdings in their self-directed investment accounts, we can provide more robust and convincing evidence on whether robo-advising generate better performance. Forth, Rossi & Utkus (2021) emphasize robo-advising's beneficial impact of portfolio diversification and index fund, and Bianchi & Brière (2021) emphasize the importance of portfolio rebalancing. Our study further finds that robo-advising also improves investor performance by avoiding investors' behavioral biases in fund choice.

2.2 Financial education

According to the household finance literature, individuals with higher financial literacy can better invest in capital markets, with high stock market participation (Van Rooij et al., 2011), more diversified portfolios (Calvet et al., 2007; Gaudecker, 2015), better portfolio rebalancing (Guiso & Vivano, 2015; Bianchi, 2018), and better investment performance (Gaudecker, 2015; Bianchi, 2018). As a result, both academic researchers and policy makers support financial education to improve households' financial literacy so that they can equally benefit from financial service (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 Personal

Financial Management Course in the US Army, Skimmyhorn (2016) find that the course and its enrollment assistance substantially increase retirement savings rates and average monthly contributions. The field experiment study by Song (2015) randomly assigns some households in rural China to a financial education treatment emphasizing the concept of compound interest and the treatment increases the pension contribution by roughly 40%.

Some other studies doubt the effectiveness of financial education in improving literacy. 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 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 the relationship of financial literacy and of financial education to financial behaviors in 168 papers covering 201 prior studies, and find that financial education has a very modest effect on financial behaviors, with even lower effect on low-income households. They propose two possible reasons for the weak effect: financial education explored by existing studies are more about content knowledge rather than financial skills, and investors are difficult to apply knowledge into investment decisions; the education effect decays over time. Therefore, they suggest future study 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 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. It is "just-in-time" in that we examine exactly the short-period effect right before versus after investors adopt the service.

Opposite to Fernandes et al. (2014), another meta-analysis paper by Kaiser et al. (2021) summarizes 76 more recently published experimental studies and show that financial education programs have, on average, positive causal treatment effects on financial knowledge and downstream

financial behaviors. Since all studies reviewed in their paper are experiments that rely on self-reported survey data, they call for future research to use administrative data for 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-class and younger households. This feature of our data ideally fits the purpose of financial education that aims to improve the sophistication of small and naive investors that have extremely limited access to traditional financial advisory service. 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

Existing literature has mixed evidence on whether traditional financial advisory leads to better investment performance (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. Together with Rossi & Utkus (2021), we find that robo-advising portfolios perform better with significantly higher Sharpe Ratio, suggesting that robo-advising can more effectively improves investment performance than traditional financial advisory.

Furthermore, we find that robo-advising can better rebalance portfolios, exhibit less extrapolation bias, availability bias and tail return overweight in fund choice. In contrast, traditional human financial advisory is criticized to display behavioral biases in fund choice and induce too many trades due to human advisors' self-interest incentive. 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 the joint venture of Vanguard and Ant Group and its robo-advisor is launched in April 2020. It is the Chinese counterpart of Vanguard's PAS, which is the world's largest robo-advisor as of the end of 2020. Ant Group operates Alipay, the once online payment platform and now the one-stop "super app" that covers almost all demands people possibly have in everyday life, ranging from ride-sharing to utility bill payment and to mutual fund investment. The BangNiTou app is integrated into Alipay app, whereby all the Alipay's one billion users can access to BangNiTou simply by several clicks. Figure 1 presents detailed steps by which Aplipay users can access to BangNiTou in the Alipay app.

[Insert Figure 1 Here]

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

Personalization of the advice: Robo-advisors vary dramatically on the extent to which they can create individually designed investment portfolios and financial plan. Similar with US commercial robo-advisors such as Wealthfront, Betterment, and Vanguard' s PAS, BangNiTou tailors investment strategies on the basis of 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 has this design.

Investor involvement: A second aspect that distinguishes different types of robo-advisors is investor involvement. The robo-advisor in D'Acunto et al. (2019) and Bianchi & Brière (2021) ask investors to approve every single 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 in time. Similar with Vanguard 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.

Investor discretion: Discretion is investors' ability to override robo-advisors' recommendation. There is no investor discretion for some robo-advisors that take full automation in implementing strategies, such as Wealthfront and Betterment. At the other end of the spectrum is the stock portfolio optimizer studied in D'Acunto et al. (2019) whereby the investor has the full discretion to adjust the portfolio recommended by the robo-advisor. BangNiTou is in the middle: at the stage of signing up, BangNiTou recommend each subscriber an investment strategy meant to fit her, but it leaves 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%; besides, 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 be trying to reduce their exposure to risk. Similar with Wealthfront and Betterment, BangNiTou is purely automated and investors cannot access any face-to-face communication with human advisors. Not employing human advisers allows these robo-advisors to maintain their operating costs low. Fully-automated robo-advisors cater to younger cohorts such as millennials, who are generally comfortable with having their wealth managed by algorithms.

BangNiTou regularly provide 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 not only for higher return but also for self-improvement and acquiring 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 BangNiTou App.

[Insert Figure 2 Here]

4. Data, sample and descriptive statistics

4.1 Data and sample

We first randomly select 100,000 BangNiTou subscribers, from the population of approximately 1 million investors who adopt BangNiTou from July to December 2020, as the treatment group. For the control group, we select 300,000 investors from Alipay users that used to buy mutual fund but do not adopt BangNiTou using stratified sampling based on demographic characteristics including gender, age, tier of the city they reside in and the amount of asset. Then we construct a 1:1 control group using PSM method based on their investment behavior characteristics.

Stratified sampling is used to obtain the control group most similar with the treatment group in terms of demographic characteristics. It 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. Distribute evenly all the investors into 120 groups based on gender, age, city tier and the average amount of asset during April and Jun 2020 (2 groups for gender, 2 groups for age, 3 groups for city tier and 10 groups for amount of asset). 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.

The PSM is conducted based on a series of investment characteristics over the 12 months before subscribing BangNiTou, including the amount of asset, style-adjusted portfolio return, style-adjusted portfolio volatility, style-adjusted Sharpe Ratio, the proportion of money market fund in the asset,

the proportion of equity fund in the asset, the proportion of bond fund in the asset, the proportion of index fund in the asset, Herfindal index of the portfolio, the correlation of 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 1 July 2019 to 31 March 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 of at least three months; (2) and at least three transactions both before and after adopting the robo-advisor. After this procedure as well as dropping observations with missing control variables, we finally have 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 details of matching procedures. Definitions of variables are presented in Appendix.

4.2 Descriptive statistics

Table 1 presents descriptive statistics of characteristics of BangNiTou adopters during the twelve months before the adoption. 29.6% of adopters are female, lower than the 47% female investors in Vanguard's PAS. 58.7% of investors reside in the largest 14 cities including Beijing, Shanghai, Guangzhou, Shenzhen, Hangzhou and so on. The mean (median) if age is 30.84 (29), far below the ages of robo-advising adopters in the US (63), France (48) and India (48), and more than half adopters are between the range of 25 and 35 years old, suggesting the majority of robo-advising users in our study are younger cohort. The mean of the amount of the adopter's asset is RMB 67,665 ($10,572), also far lower than the amount of $588,246 in Vanguard's PAS. The median is RMB 24,272 ($3,792), even lower than the amount of $282,450 in Vanguard's PAS. The mean (median) of adopter's investment size in Rehery & Sokolinski (2021) is $265,210 ($100,000) even after the robo-

advisor lowers its minimum investment. Therefore, the robo-advisor adopters in our study are significantly younger small investors with much less asset under management[9]. This demographic feature of investors facilitates us to explore whether robo-advising effectively improves performance for small investors that used to have limited access to traditional financial advisory. 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 have important implication on financial education literature.

As reported in Table 1, the proportion of wealth in money market fund (Yuebao in Aplipay) and wealth management products (WMPs) is higher than 58%, and mutual funds account for about 40% of the wealth[10]. The average monthly investment in mutual fund is RMB 23,327, the average number of fund holdings is 6.8. Of the fund holdings, 26.5% are debt funds, 70.4% are equity funds, 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 these 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 8 months after subscribing BangNiTou, including both self-directed accounts and the accounts delegated to the robo-advisor. The average size of investment increases dramatically to RMB113,087, suggesting that Alipay users generally invest more through the Alipay app over the sample period, consistent with the fact that fintech giants are increasingly penetrate into household wealth management in recent years. Investors increase mutual fund investment, with the share of mutual fund holdings changing from

[9] The average investment size in the French robo-advisor from Bianchi & Brière (2021) is 36,140 Euro dollar (roughly $39,393). This number is 1.1 million Rupee (roughly $14,300) in D'Acunto et al. (2019).

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

39.7% to 47% and the amount of fund investment more than double. The average number of fund holdings increases to 12.46. The share of debt fund in total mutual fund investment drops to 15.1% while the share of equity fund in total mutual fund investment rises to 80%. The share of index fund 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 asset delegated to BangNiTou is RMB 4,584 (1,026), which is 6.45% (2.39%) of the total investment in Alipay, suggesting that on average, investors regard BangNiTou as part of their portfolio and they only allocate a small portion in it. The median of BangNiTou account turnover is 44.7%, lower than the median of investors' self-directed account turnover. Adopters have full access to all the content in BangNiTou app, which makes it possible for the robo-advisor to play a role of financial education. 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 login 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 has 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 sophistication.

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

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 portfolio with adopters' self-directed portfolios before the 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 the adoption. Besides, 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 of adopting robo-advising, so the better performance may overstate the positive effect.

We measure performance from three dimensions, investment return, volatility and Sharpe ratio. All measures are based on individual account data and aggregated at the monthly level. Volatility is the standard deviation of portfolio daily return of the month. 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 fund and debt fund, respectively, and then calculate the benchmark performance for the style as the weighted average performance of debt and equity fund portfolio, 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 also 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 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 robo-advising portfolio is significantly lower than that of the self-directed portfolio both before and after the adoption, indicating that BangNiTou improves investment performance, measured as Sharpe ratio, mainly through lowering portfolio volatility. These findings echo and reinforce the conclusion of Rossi & Utkus (2021) by showing that robo-advising portfolios perform better than investors' own portfolios both before adoption and of the same period. The economic magnitude of the improvement in performance is also large, with monthly average Sharpe ratio increasing from -0.049 (before the adoption) to 0.041 (after the adoption), suggesting that robo-advisors are also beneficial to small investors that are more naive and have much limited access to financial advisory service.

[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 each month after the adoption. The style-adjusted volatility of BangNiTou accounts is lower than that of the adopters' self-directed accounts in almost each month after the 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 better invest in risky assets.

[Insert Figure 3 Here]

Robo-advising and portfolio changes

This part 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 fund 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 fund (Sharpe, 1991; Pederson, 2018), especially net of the fund management fee, and small investors have little expertise in fund choice, so investing in low-management-fee index funds are beneficial to small investors.

According to Panel B and C, the robo-advisor lowers the percentage of equity fund in mutual fund holdings from about 70-80% to about 60%, and raises the percentage of debt fund from roughly 20% to 40%. Now that BangNiTou tailors investment strategies after considering investors' risk preferences, investors in Alipay seems to invest excessively in equity fund 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]

Robo-advising and investment behaviors

Behavioral finance and household finance literature points out that behavioral biases are one important reason for individual investors to incur loss (Bailey, Kumar & Ng, 2012; Barber & Odean, 2013; Beshears et al.,2018). Robo-advising manages portfolio following algorithms and is supposed to be able to avoid behavioral biases. In this part, we investigate behavioral biases in fund choice, portfolio management and rebalance, three aspects that are more likely to be improved by the robo-advisor and less affected by investor discretion[11].

[11] Bailey et al. (2012) investigates individual investors' behavioral biases in mutual fund investment. Barber & Odean (2013) review research on individual investor behavioral biases. Beshears et al. (2018) review household finance literature related with behavioral biases. These studies reveal that behavioral bias leads to trading loss, including disposition effect (Odean, 1998), over trading (Barber & Odean, 2000), under diversification (Goetzmann & Kumar, 2008), attention-grabbing trades (Seasholes & Wu, 2007; Barber et al.,

Prior literature documents that individual investors under-diversify their portfolios (e.g., Goetzmann & Kumar, 2008). We measure the extent of diversification by Herfindal index of mutual funds held in the portfolio and the correlation in fund returns. Specifically, if the ratio between 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: regress each fund's daily return on the portfolio's daily return to obtain the R^2 of the regression; 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 diversified.

framing bias refers to the pattern that investors buy and sell individual assets without considering total portfolio effect (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 individual asset trading and the higher the framing bias.

We also include behavioral biases in fund choice, 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 return or turnover over the recent past and funds with most advertisement. We define a fund to be attention-grabbing if it is ranked in top 10 percent best performance over the last month or top 10 percent subscription over the last month. Extrapolation bias is the tendency to take a recent experience and project that it will continue into the future. 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

2021), over-extrapolation bias (Greenwood & Shleifer, 2014; Da et al., 2021), tail returns overweight (or trading for lottery) (Kumar, 2009; Akbas & Genc, 2018; Clifford et al., 2021). Vanguard report suggests that eliminating behavioral biases contributes to 50% increase in net return (Kinniry et al., 2014). We did not examine behavioral biases including disposition effect and over trading, because BangNiTou adopters keep the discretion to quit the service at any time. Besides, when investors adopt robo-advising is also affected by their timing decision.

mutual funds (ranked top 20% among 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 that investors 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 6 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 behavior 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 under diversification. 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 signing up, suggesting that the robo-advising further diversifies portfolios, consistent with the findings of prior literature that financial advisory contributes 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 the framing bias, as evidenced by the lower framing bias of robo-advising portfolios than self-directed portfolios both before and after the adoption. Bianchi & 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 the investors' self-directed accounts both before and after the adoption. These behavioral biases are also exaggerated by brokers' marketing strategies that usually cater to investors and promote mutual funds that outperform recently or have extremely high historical return. 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]

Who benefit more from adopting robo-advising?

This part explores who benefit more 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 the size of total wealth in Alipay, the ratio of the value of equity fund to total wealth, the ratio of the value of index fund 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, channels of signing up, value of the robo-advising portfolio, share of BangNiTou account in the investor's Alipay account. Variables of portfolios and investment behaviors are the average of the 12 months before signing up.

Results are reported in Table 5. 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 fund 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 an 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, namely, the financial education role of robo-advising. The survey study by Rossi & Utkus (2020) show that robo-advisors can serve as a empowering tool that contributes to investors' self-improvement and financial literacy. We propose BangNiTou to be a powerful education tool based on its two features. First, the financial education in prior literature is more about financial knowledge, and investors, especially naive investors, are difficult to apply the knowledge into their financial decisions (Fernandes et al., 2014); in contrast, robo-advising is such an education tool less about general knowledge and more specifically about how to manage one's mutual fund portfolio. BangNiTou regularly updates reports for portfolios and strategies in its app and adopters can access

to the detailed portfolio information at any time. It sets models of mutual fund portfolios that are easy for investors, especially naive investors, to follow. Besides, BangNiTou app post articles on investment guidance that are instructive for investors to improve their investment skills in the form of service notes. The content of these articles includes, for instance, how to diversify one's portfolio, balance risk and return, what behavioral biases investors may have, how to avoid mistakes in investment, and so on. It also posts articles that relieve investors' anxiety, stress and depression after market turmoil so as to improve their mental well-being and avoid irrational trading.

Second, the robo-advisor intensifies the education effect through its repeated interaction with investors. The effect of investor behavior interventions decays over time (Fernandes et al., 2014), so repeated interaction can reinforce the education effect. 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 through 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 app. The effect is especially stronger for the younger tech-savvy investors that trust fintech and rely on online platforms to improve their financial literacy (Hong et al., 2021).

Regression model

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

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

The dependent variables are measures of behavioral biases in fund choice and portfolio management. Post is defined to be 1 for observations after the signing up and 0 otherwise. The monthly observations used in previous sections of the study are averaged into investor-period level for this specification. Individual investor fixed effect is 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 signing up and 0 otherwise.

Second, we use the DID research design to examine the financial education effect on adopters relative to the control group. Details on the control group construction please refer to data and sample in section 4. The regression model is following:

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

Treat is defined to be 1 for investors 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 group. Individual investor fixed effect is included in all specifications. Details of variables in each specification are as follows:

In the portfolio diversification test, we use Herfindal index of the mutual 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 fund in the 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 fund 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, availability bias. We control for variables including the size of wealth, style-adjusted portfolio return, style-adjusted volatility, the share of equity fund in the wealth, HHI of the portfolio, framing bias, and portfolio turnover.

Empirical results

Table 6 presents results for the Probit model of what characteristics determine the 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 the robo-advisor. Demographic characteristics, such as gender, age and city of residence, should affect investors' decision 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 in MMF and WMPs and less in risky assets are more likely to adopt robo-advising. Investors that 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 that 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. Besides, investors trading more frequently and more overweight tail returns are more likely to adopt robo-advising.

[Insert Table 6 Here]

Contrary to our findings, evidence in the US seemingly suggests that more naive investors are more likely to adopt robo-advising. Rossi & Utkus (2021) document that investors whose self-directed accounts perform worse are more likely to adopt robo-advising. Reher & Sun(2019) find

that investors ex ante under diversifying their portfolios are more likely to signing up for and invest more in robo-advising after the robo-advisor lowers minimum investment. Investors' demographic characteristics may be one explanation for the discrepancy between US evidence and our findings. Integrated in Alipay app, the super app that penetrate to almost every household in China, BangNiTou can be accessible to a large number of small investors that are less financially literate and have limited access to human financial advisory. 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) 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 Column (1), (3) and (5) are significantly negative, indicating that the adopters have more diversified mutual fund portfolios 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 take more diversified portfolios and display less framing bias after adopting robo-advising.

We evaluate the economic magnitude of financial education effect using the thresholds proposed by Kraft (2020): less than 0.05 standard deviation is small, 0.05 to less than 0.20 is medium, and 0.20 or greater is large. The economic magnitude of the effect on diversification is 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 5.1% decrease in Herfindal index of the adopter's self-directed portfolio, equivalent to 0.2 standard deviation of 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 deviation 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 choice. Column (1) and (2) presents 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 the tail return overweight. The changes in extrapolation bias are similar. Investors display less availability bias after adopting robo-advising, and even lower compared with the non-adopters. Collectively, evidence in this part suggests that investors learn from robo-advising and exhibit less behavioral bias after interacting with the robo-advisor.

However, the economic magnitude of effect on behavioral biases in fund choice are generally lower than in portfolio management (under diversification and framing effect), with 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 mind and behaviors, intentionally or subconsciously, by mimicking the robo-advising portfolio. Second, investors' behavioral biases in fund choice are also related to brokers' marketing strategy that exploit rather than rectifying investors' biases to maximize their own sales revenue, and robo-advising's impact is partly offset.

[Insert Table 8 Here]

[Insert Figure 6 Here]

Then 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-adopting 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 low pre-adopting diversified portfolio improve more in portfolio diversification after adopting robo-advising. As reported in all six columns of Table 9, we find that except for framing effect, low-sophistication investors improve more in the other five aspects of investment behaviors, indicating that robo-advising's education effect is greater among more naive investors.

[Insert Table 9 Here]

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 difference between robo-advising adopters and non-adopters, and the effects we document is driven by such difference rather than the robo-advising's education role. PSM sample along with individual investor fixed effect 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 in a financial program that both improves their financial sophistication and promotes the benefit of delegating investment to professional advisors at the same time. 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. In this section we address this concern by exploring BangNiTou's marketing programs.

Investors join in the robo-advisor through multiple channels. Approximately 60% investors sign up for BangNiTou through the Alipay wealth management app, 10% investors search for and then participate in BangNiTou, and nearly 30% adopters are attracted by BangNiTou's promotion campaigns that offer coupons to lower subscription fees by 50% to 100%[12]. Now that many investors regard BangNiTou as one wealth management product alternative to mutual funds, the subscription coupons can indeed attract them to invest in BangNiTou without fully recognizing the difference between robo-advisors and mutual funds. As a result, we treat the investors that join in robo-advising through the promotion campaigns as a clean subset of adopters that are ex ante indifferent with non-adopters, and then construct the matched sample in the same way as in the main results. Individual investor fixed effect is also included.

Table 9 reports the results. All coefficients of $Treat_i \times post_i$ are statistically significant except in Column (5), indicating that the positive education effects documented in the main results are largely robust. It should also be noted that the economic magnitudes for most specifications are almost unchanged, suggesting that the unobserved time-variant factors are not a major concern in our setting.

[Insert Table 10 Here]

6. Mechanisms of robo-advising's education effect

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

6.1 Repeated interaction intensifies the education effect

[12] The typical promotion is the pop-up ads that Alipay users can see whenever they log in the Alipay wealth management app, highlighting the discount of subscription fees and reminding investors that they can sign up now to enjoy the discount.

Prior literature points out that the forms of financial education that are one-off and about general knowledge have limited effect on such sophisticated decisions as portfolio management (Duflo & Saez, 2003; Lusardi & Mitchell, 2014). In contrast, BangNiTou provides investors opportunities of repeated interaction with financial advisory 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 to the content of service notes any time they want to log in the app, and highlights of important tips are posted in the first page of the app. In this way BangNiTou reinforces its education effect through the intensified interaction with investors. Therefore, we predict that the education effect is stronger for investors staying longer time with BangNiTou app.

We include the interaction term of post and the length of staying in the BangNiTou app in equation (1), the variable of interest capturing the cross-sectional variation in investors with different level of interaction with the robo-advisor. Results are reported in Table 11. The significantly negative coefficients in Column (1), (3) and (4) indicate that investors staying longer time in BangNiTou app have more diversified portfolio, display less framing bias and tail return overweight. There is no result for extrapolation bias and 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 11 Here]

We use the time investors spend in learning about robo-advising before signing up as another proxy for the intensity of interaction. Investors spending longer time in reading information about the robo-advisor are more likely to be affected by robo-advising. Results reported in Table 12 generally support our prediction. The coefficients of the interaction term *post*Subscription time (1/0)* are

significantly negative in 4 out of 6 columns. Investors that spend longer time in learning BangNiTou have more diversified portfolios, and display less framing bias and availability bias.

[Insert Table 12 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 choice. Investors can learn robo-advising portfolios by reading BangNiTou's quarterly portfolio reports, so in this part we analyze how investors learning from the robo-advisor by comparing investment behaviors between investors that have read the reports and those not. Learning behavior is depicted through five aspects in the investor's self-directed investment account: the share of the subscription of mutual funds that appear in her recent BangNiTou portfolio; the share of the subscription of mutual funds increasingly held by her recent BangNiTou portfolio; the share of the redemption of mutual funds decreasingly held by her recent BangNiTou portfolio; the share of the subscription of mutual funds managed by fund companies that appear in her BangNiTou portfolio; the similarity index in investment style between her self-directed portfolio and BangNiTou portfolio, constructed based on measures including market factor, size factor, evaluation factor, momentum factor and exposure to industry.

Table 13 depicts the differences in learning behaviors in their self-directed accounts between investors that read BangNiTou portfolio reports and those not. Investors that read the report buy more mutual funds that appear in their recent BangNiTou portfolios, more funds increasingly held BangNiTou portfolios and managed by fund companies appearing in BangNiTou portfolios, sell funds that BangNiTou holds less, and have more similar investment style with BangNiTou. Collectively, these findings are consistent with that investors learn from robo-advising by following portfolio model set by BangNiTou. For instance, in the first quarter after adopting BangNiTou, on average, the share of mutual funds appearing in BangNiTou portfolios subscribed by investors that

have read BangNiTou reports is 1.11%, significantly higher than that for investors having not read reports (0.92%). The patterns are similar for the second and third quarter.

[Insert Table 13 Here]

To solidify the easy-to-follow argument, we further conduct a placebo test by examining the learning effect though service notes. Service notes contain financial knowledge and investment instructions useful to improve investor sophistication, but different from portfolio reports, investors need to learn how to apply them into practice rather than simply imitation. In other words, service notes are not so easy to follow as BangNiTou portfolios. If the easy-to-follow feature is important, we would see a discrepancy in 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 not in four of the five aspects except for the 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 Alipay mobile phone app. Robo-advising has both direct and spillover effect on adopters. Robo-advising portfolios bring investors better investment performance with lower volatility and higher Sharpe ratio. Besides exploiting the benefits of diversification and index investment, mitigating behavioral biases in fund choice and portfolio management is one important channel through which robo-advising have better performance.

More importantly, robo-advising has significantly positive externality: it improves investor sophistication. After adopting robo-advising, investors take more diversified portfolios and exhibit fewer behavioral biases in fund choice and portfolio management in their self-directed accounts. Interestingly, the economic magnitude of reduction on behavioral biases in fund choice is much

lower than that of portfolio management, suggesting that more efforts should be taken to protect retail investors from cognitive biases in the process of fund sales.

Furthermore, the spillover effect is more prominent for adopters that interact with the service more actively and that used to be less rational beforehand. We also find evidence that adopters learn from robo-advisors 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, shedding lights on research and practice in financial education.

This study also has important implication on financial inclusion. Naive and low-class households have limited access to traditional financial advisory service, neither have they knowledge and skills to participate in capital market investment. 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 RMB1,000), attract many low-class and younger investors to sign up. We show that even poorer and younger investors can benefit from delegating their investment to financial advisory. However, our findings that investors only allocate a small portion in robo-advisor portfolios that have higher sharp ratio than their self-directed portfolios emphasize the importance of financial education: naive investors need not only convenient and affordable access to financial advisory service, 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 also provides empirical evidence on the effectiveness of robo-advising as a financial education tool on changing financial behaviors of households, especially poorer and younger investors, based on a large-sample administrative data set.

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Appendix: Variable Definitions

Female: a dummy variable that equals one if the investor is a woman and zero otherwise.
Age: the age of an investor
Top city: a dummy variable that equals one if the investor resides in the largest 18 cities in China and zero 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 Asset: the amount of total asset 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 asset. *YuErBao* is the largest money market fund in China operated by Alipay's subsidiaries.
WMPs Ratio: the amount of the Wealth Management Products (WMPs) held by investor *i* at the end of month *t* divided by total asset. WMP is an off-balance-sheet substitute for deposits widespread in China with investment return and risk slightly higher than deposit but much lower than mutual fund.
Mutual Fund Ratio: the amount of mutual funds held by investor *i* at the end of month *t* divided by total asset.
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 subscription and redemption by investor *i* in month *t*.
Portfolio Turnover: the total amount of fund subscription and redemption 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 asset delegated to BangNiTou by investor *i* at the end of month *t*.
BangNiTou Ratio: the amount of asset delegated to BangNiTou by investor *i* at the end of month *t* divided by total asset.
BangNiTou Subscription: the amount of asset delegated to BangNiTou subscribed by investor *i* in month *t*.
BangNiTou Redemption: the amount of asset delegated to BangNiTou redeemed by investor *i* in month *t*.
BangNiTou Turnover: the total amount of BangNiTou subscription and redemption by investor *i* in month *t* divided by the average amount of BangNiTou asset at the beginning and end of month *t*.
BangNiTou Logins: the number of times that investor *i* log in to BangNiTou App in month *t*.
BangNiTou Stay: the length of time that investor *i* spend on 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 follow:

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

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

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 splits or dividends. The benchmark portfolio of any portfolio *i* is constructed with the same share of equity and debt fund as portfolio *i* and using market-wide average performance for equity fund and debt fund 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 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 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 to 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 of a portfolio.

Fund Correlation: the average correlation among funds in a portfolio. We first regress each fund's daily returns in a portfolio on the portfolio's daily returns in a given month to obtain the R^2 of the regression and then use the weighted average of R^2 for all funds in the portfolio as the *Fund Correlation* measure. The higher the correlation measure, the less the portfolio 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 individual asset trading and the higher the framing bias.

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

Extrapolation bias: the percentage of investor *i*'s subscription for momentum funds among all his/her subscriptions in month *t*. The 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 top 20% among 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 6 months.

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

Table 1 presents descriptive statistics of demographic characteristics, portfolio holdings, trading behaviors of BangNiTou adopters during the twelve months before the adoption. Regarding portfolio characteristics and trading behaviors, we first calculate the average characteristics of each variable for each investor during the twelve months before the 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
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 Asset	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 the adoption)

Table 2 presents descriptive statistics of portfolio characteristics, trading behaviors, and digital footprints of BangNiTou adopters during the eight months after the adoption. We first calculate the average characteristics of each variable for each investor during the eight months after the 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 25th (P25) and 75th (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 Asset	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, Sharpe ratio, monthly return, and volatility. 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 measures are 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 difference of performance between BangNiTou portfolios and investors' self-directed portfolios before (after) the adoption. The sample mean (Mean) and its standard errors (SE) in each group are reported and the values in bold are significant at 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 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. 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 with "(3)-(1)" ("(3)-(2)") display the difference of investment behaviors between BangNiTou portfolios and investors' self-directed portfolios before (after) the adoption. The sample mean (Mean) and its standard errors (SE) in each group are reported and the values in bold are significant at 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 brought by robo-advising

Table 5 explores the relation between investor characteristics and performance improvement brought by robo-advising. The dependent variable is the average difference of style-adjusted Sharpe ratio between BangNiTou portfolio and investors' self-directed portfolio from one month to eight months after adopting the robo-advising. The column (1) displays the results of demographic characteristics. The column (2) displays the results of average portfolio characteristics during twelve months before adopting robo-advising. The column (3) displays the results of average investment behavioral biases during twelve months before adopting robo-advising. The column (4) displays the results of investment behaviors related to robo-advising. The column (5) presents the results when including all variables in columns (1), (2), (3), and (4) into the regression at the same time. See Appendix A for detailed definitions of variables. *Subscription strategies* indicate dummy variables of adopted robo-advising strategies varying on the debt and equity fund ratio in the portfolio. *Subscription months* indicate dummy variables of months adopting robo-advising, which ranges from July, 2020 to December, 2020. *Subscription channels* indicate 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 brought by 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 asset)		-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 The analysis of investor characteristics that determines the robo-advising adoption

Table 6 presents results for the Probit model of what investor characteristics determine the robo-advising adoption. The dependent variable is whether the investor signs up for BangNiTou and independent variables include average portfolio characteristics and investment behaviors within the 12 months before signing up for the robo-advisor. The column (1) presents the results using the sample that consists of robo-advising adopters and non-adopters obtained from stratified sampling. The 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 asset)	-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 The 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 that 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 one for observations after the signing up and 0 otherwise. *Post* equals to 1 for observations after the robo-advisor signing 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 one for investors adopt robo-advising and 0 otherwise. Other specifications and variables are similar to that of Model (1). Individual investor fixed effect is 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 asset)	-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 The impact of Robo-advising on investors' behavioral biases in self-directed fund choice

Table 8 analyzes how robo-advising impacts adopters' behavioral biases in self-directed fund choice. We analyze the effect using two models. In Model (1), the sample only includes investors that 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 one for observations after the signing up and 0 otherwise. *Post* equals to 1 for observations after the robo-advisor signing 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 one for investors adopt robo-advising and 0 otherwise. Other specifications and variables are similar to that of Model (1). Individual investor fixed effect is 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 asset)	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 investigate whether the spillover effect of robo-advising varies on adopters' sophistication. The dependent variables are *portfolio concentration*, *fund correlation*, *framing bias*, *availability bias*, *extrapolation bias*, and *tail return overweight*, respectively. Adopters' sophistication is measured depending on investment behaviors we investigate. For example, in column headed with "*Portfolio concentration*", Sophisticated (1/0) is defined to be one if an adopter's average portfolio concentration during twelve months before signing up for robo-advising is lower than the sample median and zero 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 asset)	-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 The impact of robo-advising on investors'self-directed investment behaviors using the sample of adopters attracted by promotion campaigns

Table 10 analyzes the impact of robo-advising on investors' self-directed investment behaviors by focusing on the adopters attracted by BangNiTou's promotion campaigns. We estimate the effect using Model (2) introduced in section 5.2.1. 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	1.2171***	0.8397***	-0.4498***	0.4643***	0.4292***	0.0514***
	0.0163	0.0147	0.1013	0.0086	0.0299	0.0124
Post	-0.0261***	-0.0262***	-0.1196***	0.0432***	0.1559***	0.0076***
	0.002	0.0019	0.0116	0.001	0.0036	0.0014
*Treat*Post*	-0.0454***	-0.0398***	-0.2133***	-0.0113***	-0.0057	-0.0066***
	0.0024	0.0022	0.0151	0.0012	0.0043	0.0017
Log (Total asset)	-0.0635***	-0.0205***	-0.1111***	0.0023***	0.0028	0.0061***
	0.0016	0.0014	0.0092	0.0008	0.0027	0.0011
Style-adjusted Sharpe ratio	0.106***	0.1427***	0.1302***	-0.0531***	-0.1175***	0.0259***
	0.0094	0.0093	0.0455	0.0048	0.0152	0.0064
Equity fund ratio	-0.187***	0.0891***	-0.3771***	0.1307***	0.1931***	0.0721***
	0.0056	0.0049	0.0325	0.0027	0.0093	0.0039
Portfolio concentration			1.5248***	0.0099***	-0.1033***	-0.0423***
			0.0351	0.0032	0.0109	0.0045
Framing bias	0.0387***	0.0071***		-0.0017***	0.0113***	-0.001
	0.001	0.0008		0.0004	0.0014	0.0005
Tail return overweight	0.0061***	-0.0405***	-0.0429***			
	0.0015	0.0014	0.0079			
Extrapolation bias	-0.0255***	0.0298***	0.1353***			
	0.0036	0.0033	0.0182			
Availability bias	-0.0758***	0.0331***	-0.1537***			

	0.0097	0.0088	0.0444			
Portfolio turnover	0.0126***	-0.0141***	-0.0951***	0.0035***	0.0147***	0.0146***
	0.0011	0.001	0.0054	0.0006	0.0017	0.0009
Investor FE	Y	Y	Y	Y	Y	Y
Obs.	68412	68412	68412	68412	68412	68412
Adjusted R^2	0.3889	0.1105	0.1919	0.2529	0.202	0.0501

Table 11 Interaction intensity and the spillover effect: Evidence from BangNiTou Stay

Table 11 explores how the intensity of investors' interaction with robo-advising influence the spillover effect. In this table, the interaction intensity is proxied by the monthly average length of time that an investor spent on BangNiTou App. We estimate the effect by adding an interaction item "*Post*BangNiTou stay (1/0)*" into Model (1). *BangNiTou stay (1/0)* equals one if an adopter's monthly average *BangNiTou stay* is larger than the sample median and zero 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	1.3224***	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 asset)	-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 12 Interaction intensity and the spillover effect: Evidence from time spent on signing up for robo-advising

Table 12 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 one if an adopter's *Subscription time* is larger than the sample median and zero 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 asset)	-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 13 Evidence on adopters mimicking investment behaviors of robo-advising

Table 13 examines whether adopters mimicking 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 not. Mimicking behaviors are depicted from five aspects: 1) the percentage of the subscription of mutual funds that appear in recent BangNiTou portfolios; 2) the percentage of the subscription of mutual funds held more by recent BangNiTou portfolios; 3) the percentage of the redemption of mutual funds held less by recent BangNiTou portfolios; 4) the percentage of the subscription of mutual funds managed by fund companies appearing in recent BangNiTou portfolios; 5) the distance in investment style between investors' self-directed portfolios and their BangNiTou portfolios. 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 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 report and those not and the corresponding t-statistics.

	1st Quarter	2nd Quarter	3rd Quarter
Whether to read BangNiTou portfolio report	The percentage of the subscription of 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
	The percentage of the subscription of mutual funds held more 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
	The percentage of the redemption of mutual funds held less 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
	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
	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


总资产
我的三笔钱
专属理财师邀请函，请查收！
68,658.12
昨日收益 -1,686.50
灵活取用
稳健理财
进阶理财
0.00
0.00
68,658.12
0.00
0.00
-1,686.50
资产明细
余额
0.00
余额宝
能赚又能花
理财产品
收益稳健
基金
66,902.56
-1,663.13
黄金
买入0费率
帮你投
1,755.56
-23.37
去看看更多理财产品


帮你投
全面进攻策略
总金额(元)
1,755.10
昨日收益(元)
-23.37
持有收益(元)
+107.67
累计收益(元)
+107.92
交易记录
资产报告
我的定投
你的金牌智能助理上线啦！
你的专属智能助理上线啦！
累计盈亏
策略业绩
2021-12-21
转出
定投
转入


帮你投
近3月
近6月
近1年
持有以来
当前账户配比
我的策略
账户配比健康
股票类基金 90.23%
固收类基金 9.77%
服务笔记
更多
今日市场为何下跌，如何...
常见问题
联系客服
转出
定投
转入


全面进攻策略
季末配置明细
股票类基金
90.17%
增强与主动基金
中欧新趋势混合(LOF)A
10.17%
汇添富价值精选混合A
9.58%
富国沪深300增强A
9.21%
景顺长城沪深300增强
6.08%
富国中证500指数增强(LOF)A
5.90%
权益指数基金
嘉实沪深300ETF联接(LOF)A
29.17%
南方中证500ETF联接(LOF)A
华夏恒生ETF联接(QDII)C
固收类基金
9.83%
信用债基金
易方达高等级信用债债券A
3.90%
利率债基金
华夏亚债中国指数A
5.93%

Figure 2 Overview of service notes on BangNiTou App

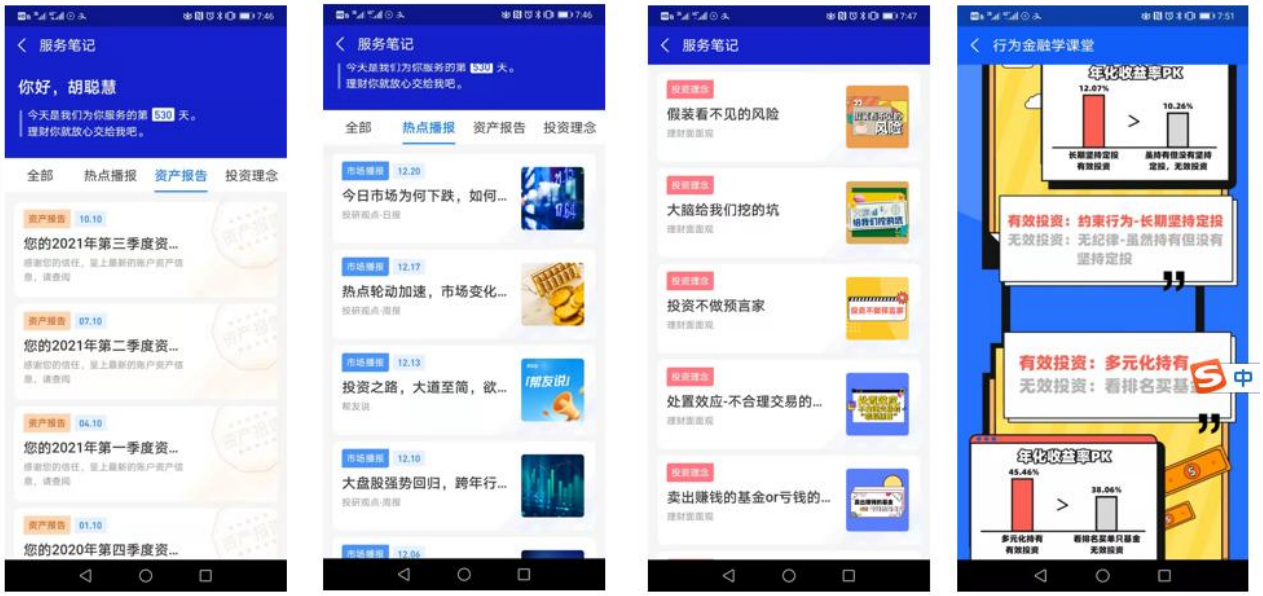


Figure 2 presents screenshots of service notes in BangNiTou app. The first screenshot from the left is the quarterly portfolio reports pertained to the specific investor. The second screenshot from the left contains articles aiming to help investors understand the market fluctuation and manage emotions. The third screenshot contains articles about investment principles, e.g., investment risks ignored, the traps set by our cognition, and tips on how to overcome behavioral biases. The fourth screenshot is about a learning center of 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

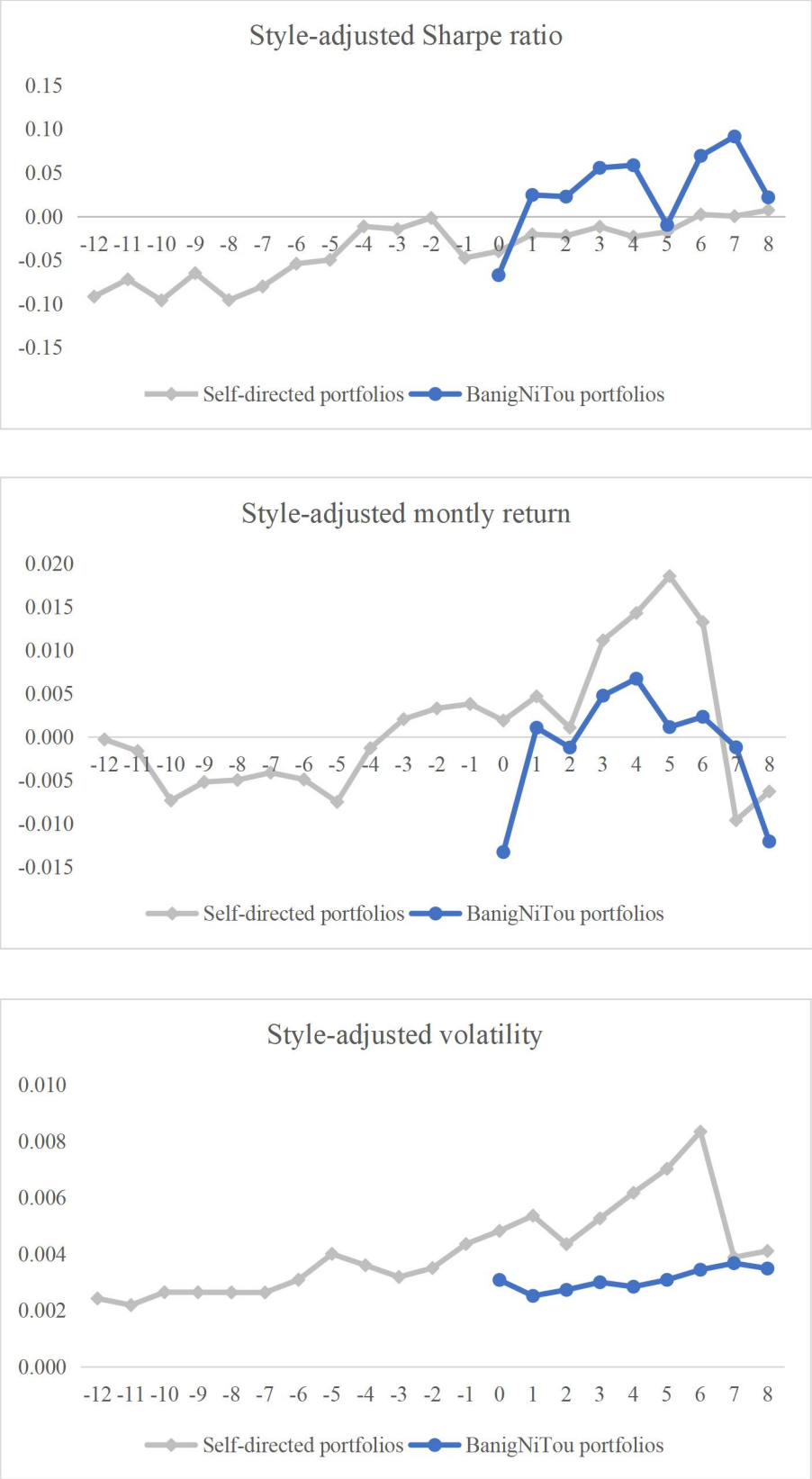


Figure 3 plots the style-adjusted investment performance for delegated BangNiTou portfolios and investors' self-directed portfolios from twelve months before to eight months after adopting the robo-advisor. Investment performance is measured by style-adjusted Sharpe ratio, style-adjusted return, and style-adjusted volatility, respectively.

Figure 4 Portfolio characteristics: Self-directed portfolios vs. BangNiTou Portfolios

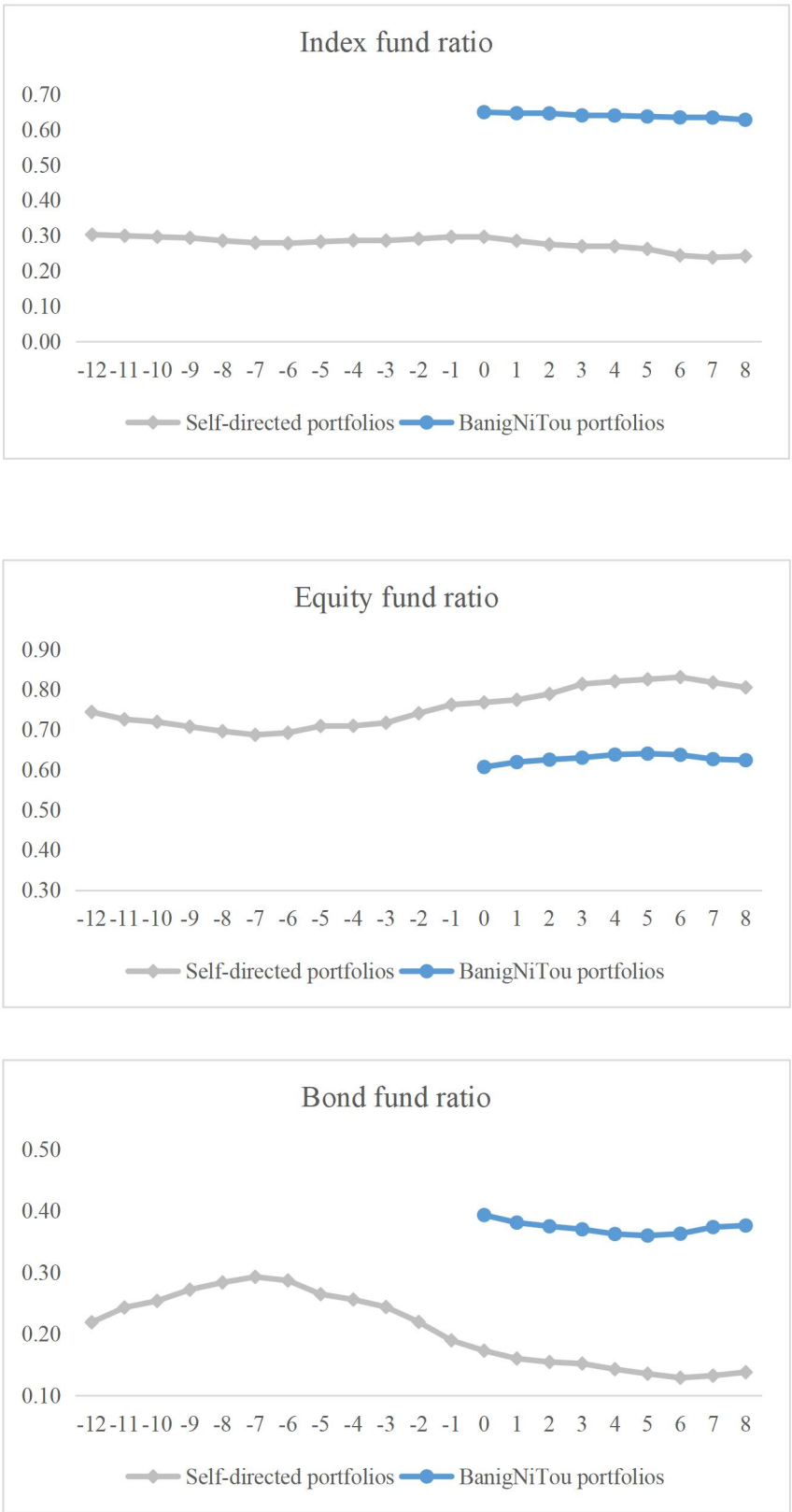


Figure 4 plots portfolio characteristics for delegated BangNiTou portfolios and investors' self-directed portfolios from twelve months before to eight months after adopting the robo-advisor. Portfolio characteristics include index fund ratio, debt fund ratio, and equity fund ratio.

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

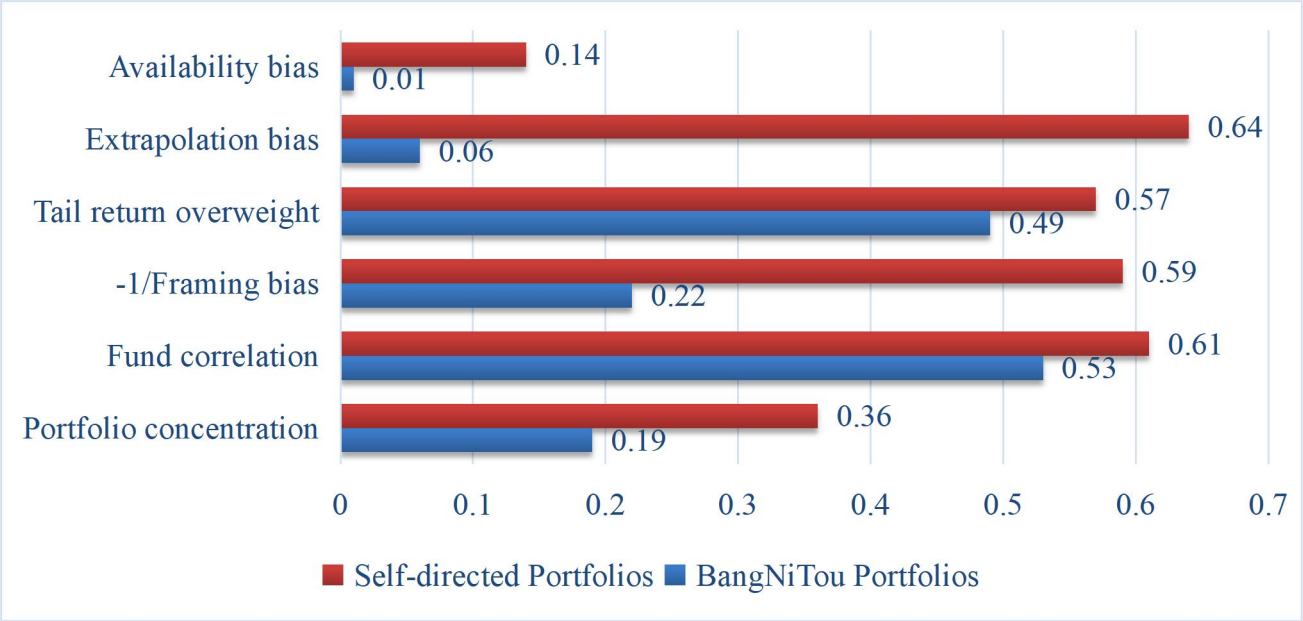


Figure 5 compares the average investment behavioral biases for delegated BangNiTou portfolios and investors' self-directed portfolios from one month to eight months after adopting the robo-advisor.

Figure 6 The economic significance of spillover effects

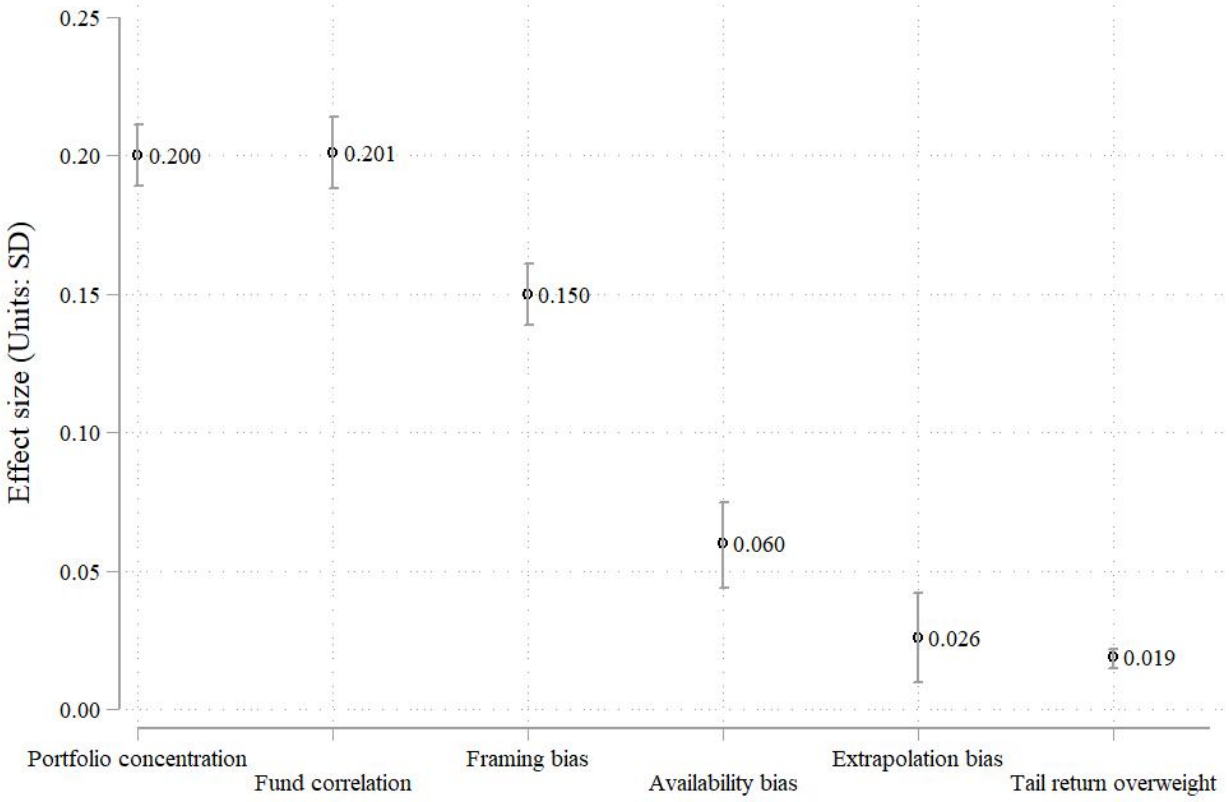


Figure 6 compares the economic significance of the spillover effect on different behavioral biases. For each behavioral bias, the effect size is defined to be the estimated coefficient using Model (2) in Table 7 or Table 8 divided by the sample standard deviation of the behavioral bias in our sample.