The Demand for Robo-Advising: Adoption and Delegation Intensity

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March 12, 2026

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Abstract

Empirical studies of robo-advisor adoption report conflicting findings about who uses automated investment advice. We argue that these contradictions arise from conflating two distinct decisions: whether to adopt robo-advice and, conditional on adoption, how much wealth to delegate. Using 49 months of proprietary panel data on 100,000 Chinese investors on Alipay, we show that the determinants of these two decisions are not merely different but frequently opposite in sign. Older and more experienced investors are more likely to adopt yet delegate significantly less, consistent with sophistication lowering discovery costs while raising the opportunity cost of ceding control. Underdiversified investors are less likely to adopt but, conditional on adoption, delegate substantially more, a pattern we interpret through an awareness mechanism in which biased investors underestimate the benefits of algorithmic correction until they experience it. Comparing robo-advising with automated trading on the same platform reveals that these patterns are specific to the delegation of portfolio decisions: investors readily automate execution while resisting delegation of decision authority. Selection on unobservables is positive and economically large, implying that robo-advising attracts committed delegators rather than reluctant experimenters. Our results extend the household finance literature by showing that the same-direction alignment between participation and portfolio efficiency documented in canonical work breaks down when participation involves delegating decision authority. They also reconcile the conflicting findings in the robo-advising literature by revealing that prior studies capture different margins of a single underlying demand system.

Keywords: Household Finance, FinTech, Robo-Advising, Behavioural Finance, Financial Automation

JEL Classification: G11, G41, D83, G24, O33

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The authors acknowledge and appreciate the supports from the Digital Economy Open Research Platform (www.deor.org.cn). All data was sampled and desensitised, and was remotely analysed on the Ant Open Research Laboratory in an Ant Group Environment, which is only remotely accessible for empirical analysis. We thank Chris Brooks for providing useful feedback. Jay particularly thanks Jian Hou and Wenhao Zhang from Ant Group for helping with data processing and answering technical questions. The opinions in this paper only represent those of the authors and do not necessarily represent those of Alipay or Ant Group. All mistakes are our own.

1. Introduction

Who uses robo-advisors? The empirical literature offers strikingly inconsistent answers. Several studies converge on the finding that robo-advisor users are younger, male, and hold smaller portfolios. Brenner and Meyll (2020) document this pattern using the 2015 National Financial Capability Investor Survey. Hao et al. (2022) find a similar demographic profile among Chinese investors, while also showing that more sophisticated investors benefit more from the service. Proprietary data from India confirms the same general picture: Baulkaran and Jain (2023) report that users are relatively young, male, married, and small investors. Yet other evidence contradicts each of these patterns. Belanche et al. (2019) find that neither age nor gender significantly predicts robo-advisor acceptance. D'Acunto et al. (2019) show that adopters are statistically indistinguishable from non-adopters in age, though they hold substantially higher asset values. Beyond demographics, behavioural characteristics add further complexity. Piehlmaier (2022) documents that overconfident investors exhibit significantly higher adoption propensity, and that while higher financial literacy appears to decrease uptake, unjustified confidence in one's financial knowledge causally increases it. What explains these conflicting patterns? The contradictions are especially puzzling given the growing evidence that robo-advising improves diversification, reduces behavioural mistakes, and raises risk-adjusted returns (Bianchi & Briere, 2026; Hao et al., 2022; Reher & Sokolinski, 2024; Rossi & Utkus, 2024).

We propose a simple resolution. These conflicting findings reflect a fundamental conflation of two distinct economic decisions: the extensive margin of whether to adopt robo-advice and the intensive margin of how much wealth to delegate conditional on adoption. The distinction matters. An investor who allocates five percent of wealth to a robo-advisor has adopted in a nominal sense, but the technology exerts minimal influence on her portfolio. An investor who delegates eighty percent has made robo-advising central to her financial life. Treating these investors as equivalent obscures economically consequential heterogeneity. If the two margins respond differently to the same investor characteristic, studies will report conflicting results depending on which margin dominates observed variation in their particular sample.

The idea that participation and conditional portfolio behavior represent distinct economic decisions has deep roots in household finance. Campbell (2006) emphasized that participation costs and portfolio inefficiencies are separate channels through which households deviate from normative benchmarks. Calvet et al. (2007) provided the foundational empirical evidence. They showed that the same sophistication proxies, like wealth, education, income, predict both higher participation and better diversification among participants, with effects moving in the same direction. Their finding that households who are "out" would likely be "down" if they entered established a strong empirical regularity: the characteristics that draw investors into markets also make them better investors once there. This same-direction alignment has shaped the field's understanding of how household characteristics relate to financial outcomes.

A parallel distinction appears in the technology adoption literature. Comin and Mestieri (2010) document that for general-purpose technologies such as electricity and telecommunications, cross-country variation in usage intensity dwarfs variation in adoption timing. Countries that adopted the same technology in the same decade exhibit order-of-magnitude differences in usage intensity decades

later. Robo-advising sits at the intersection of these two literatures. It is simultaneously a financial participation decision and a technology adoption decision. Both literatures suggest that treating adoption as binary may miss the most important dimension of variation.

We argue that when the participation decision involves delegating control to a technology rather than simply entering a market, the same-direction alignment documented by Calvet et al. (2007) need not hold. The same investor characteristic can plausibly exhibit opposite effects across the extensive and intensive margins. Consider investment experience. Familiarity with mutual fund products lowers information costs and facilitates discovery, increasing the probability of adoption. Yet experienced investors possess accumulated human capital in portfolio management, access to established routines, and stronger outside options. These factors limit the marginal value of delegation even as they encourage trial. Wealth presents a similar tension. Higher financial assets may reduce the proportional cost of experimenting with robo-advice. At the same time, wealth strengthens the investor's capacity for self-directed management, reducing the incremental benefit of algorithmic delegation. Behavioural biases introduce a further complication that goes beyond the fixed-versus-marginal cost logic. A natural hypothesis holds that underdiversified investors should value robo-advising as a commitment device against concentration. But the defining feature of many biases is precisely that affected investors underestimate the associated costs (Goetzmann & Kumar, 2008; Odean, 1998). If awareness of bias costs decreases in bias intensity, the investors who would benefit most from automated diversification may be least likely to adopt.

This paper develops a conceptual framework, presented in detail in Section 2, that formalizes three intuitions underlying these examples. The first intuition is straightforward. Trying a new technology and relying on it are different decisions with different costs. Trying robo-advice requires overcoming one-time discovery costs: learning that the product exists, understanding how it works, and trusting it enough to open an account. These costs are fixed. Relying on it, by contrast, means giving up something ongoing: the investor's own judgment, her sense of control, and the option to manage her portfolio as she sees fit. These costs are marginal and recur with every dollar delegated. A characteristic like investment experience can reduce the first type of cost, experienced investors already know the product landscape, while increasing the second that experienced investors have more to lose by ceding control. The result is that experience encourages adoption but discourages delegation.

The second intuition concerns behavioural biases and the role of awareness. If an investor holds a concentrated portfolio and knows that concentration is costly, she has a reason to seek algorithmic diversification. But what if she does not recognize that her portfolio is poorly diversified? In that case, she sees no problem to fix and therefore no reason to adopt. The more severe the bias, the less likely the investor is to appreciate its costs, and the less likely she is to seek correction. This creates an adverse selection problem. The investors who need robo-advising most are least likely to use it. Yet among those who do adopt, perhaps through chance exposure or a friend's recommendation, the experience of holding a diversified portfolio can be revelatory. These investors update their beliefs about the value of diversification and delegate more intensively than less biased adopters who had less to learn. The result is that behavioural biases like underdiversification reduce adoption but increases delegation conditional on adoption.

The third intuition distinguishes biases that robo-advising can correct from those it cannot. Un-

derdiversification is correctable: the algorithm constructs a diversified portfolio, and the investor observes the benefits directly. Limited attention is not correctable in the same way. An investor who delegates because she lacks time to monitor her investments remains time-constrained after delegation. Adoption does not expand her attentional capacity. For correctable biases, the act of adoption itself triggers learning, which is why we expect the two decisions to move in opposite directions. For cognitive constraints, no such learning occurs, and both decisions should move together. Section 2 formalizes these intuitions and derives the precise conditions under which each mechanism generates its predicted pattern.

We test these predictions using proprietary panel data from BangNiTou, a fully delegated mutual fund robo-advisor integrated into Alipay, China's dominant mobile payments platform. The setting offers three advantages for identification. First, investors hold delegated robo-portfolios and self-directed mutual fund positions side by side within the same application, with identical liquidity and minimal switching costs. This permits observation of both the binary adoption decision and the continuous delegation share at monthly frequency for the same investors. Second, the panel spans 49 months from September 2020 to September 2024, covering 100,000 investors and 4.9 million investor-month observations. The platform records rich investor characteristics including demographics, risk preferences, trading history, portfolio holdings, and realized returns on both self-directed and robo-advised portfolios. Third, the platform also offers automated trading, a rule-based feature that executes prespecified periodic contributions to investor-selected funds. This enables a within-platform comparison between delegation of portfolio decisions and mere automation of execution. We stratify the sample to ensure sufficient variation for studying both margins, oversampling robo-advisor adopters relative to their population frequency of approximately one percent. Monthly calibration weights restore population representativeness in estimation.

The distinction between adoption and delegation carries econometric implications. Delegation intensity is observed only for adopters, so naive estimation on the selected sample yields biased coefficients if unobservables affecting adoption correlate with those affecting delegation (Heckman, 1979). Moreover, many of the characteristics central to our analysis, including age, gender, risk preferences, are time-invariant or slow-moving. A conventional panel specification with investor fixed effects would absorb precisely the cross-sectional variation we seek to identify. We therefore employ a Fama–MacBeth procedure (Fama & MacBeth, 1973), estimating Heckman two-stage selection models separately for each of 49 monthly cross-sections and reporting time-series averages of the monthly coefficients. This framework preserves cross-sectional variation, allows coefficients to vary over time, and corrects for non-random selection into robo-advising, making it better suited to our research question than a fixed-effects panel approach.

The central finding is that the determinants of adoption and delegation frequently move in opposite directions. Fund trading experience provides the sharpest example. A one-standard-deviation increase raises adoption probability by 13.7 percent, the largest extensive-margin effect among investor characteristics. Yet conditional on adoption, the same increase reduces delegation by 51 percent of the mean. Experienced investors readily try robo-advising but delegate sparingly. Age exhibits a similar pattern. A one-standard-deviation increase in age raises adoption probability by 1.8 percentage points, contradicting the common assumption that FinTech products attract primarily young digital natives.

Yet conditional on adoption, the same increase reduces delegation by 3.1 percent of the mean. Older investors experiment with robo-advising but limit the depth of their commitment.

Among behavioural biases we tested, underdiversification produces the most economically revealing result. A one-standard-deviation increase in underdiversification reduces adoption probability by 9.1 percentage points. Yet conditional on adoption, the same increase raises delegation by 4.2 percent of the mean. This pattern supports the awareness mechanism described above: underdiversified investors undervalue algorithmic diversification until they experience it firsthand. Limited attention, by contrast, reduces both adoption and delegation with no reversal. This confirms the theoretical distinction between correctable biases and persistent cognitive constraints.

Selection on unobservables proves quantitatively important. The inverse Mills ratio coefficient is positive and highly significant, implying that unobserved factors increasing adoption propensity also increase delegation intensity. Selection raises delegation by 37 percent of mean adopter allocation. This is an economically large effect, implying that robo-advising attracts committed users rather than reluctant experimenters. The pattern varies systematically across investor types. Selection is strong among younger and less wealthy investors, for whom adoption reveals genuine demand. It is weak or negative among older and wealthier investors, for whom adoption may reflect experimentation rather than commitment.

The comparison with automated trading provides our cleanest test of whether the documented patterns reflect attitudes toward financial automation in general or toward delegation of portfolio decisions specifically. Sample adoption rates are virtually identical for the two products, but investors allocate nearly three times more wealth to robo-advising. The underdiversification pattern operates for robo-advising but vanishes for automated trading, which perpetuates rather than corrects portfolio concentration. The gender gap appears for robo-advising but not for automated trading. Selection on unobservables is large and positive for robo-advising and absent for automated trading. These contrasts indicate that resistance operates specifically at the point of delegating decision authority, not at financial automation in general.

Further analysis reveals that performance feedback is statistically detectable but economically modest, concentrated at short horizons. The clearest pattern emerges from asymmetric responses to relative performance. Positive relative performance reduces delegation, while negative relative performance has no effect. This asymmetry is consistent with self-serving attribution bias.

Decomposing participation into first-time adoption, continuation, and re-entry uncovers additional heterogeneity that the general specification obscures. Wealth dominates continuation but has no effect on first-time adoption. Most notably, the gender gap reverses completely across these margins. Female investors are substantially less likely to adopt initially. But conditional on trying, they are more likely to continue and delegate more intensively. This reversal indicates that the aggregate gender gap reflects differential exposure or initial confidence rather than underlying differences in how women value robo-advice.

This paper makes four contributions. First, we reconcile the conflicting findings in the robo-advisor adoption literature. Prior studies either measure binary adoption (Bianchi & Briere, 2026; D'Acunto et al., 2019; Reher & Sokolinski, 2024) or examine portfolio outcomes after adoption (D'Hondt et al., 2020; Hao et al., 2022; Rossi & Utkus, 2024), but neither strand models the in-

vestor's choice of how much to delegate conditional on adoption. We show that these two bodies of work capture different margins of a single underlying demand system. The same characteristic can exhibit opposite effects depending on which margin dominates observed variation, and coefficient estimates that pool both margins will be attenuated as opposing forces partially offset. Our decomposition provides a unified explanation. Sophistication facilitates discovery but limits commitment, while behavioural biases impede discovery but intensify commitment among those who adopt. This reconciliation implies that the inconsistencies documented across prior studies may reflect compositional variation in the mix of extensive- and intensive-margin responses rather than genuine differences across institutional settings.

Second, the documented opposite signs extend the household finance literature on participation and portfolio choice (Calvet et al., 2007; Campbell, 2006; Haliassos & Bertaut, 1995). As noted above, Calvet et al. (2007) established that the same sophistication proxies predict both higher participation and better diversification, with effects moving in the same direction. This alignment created a natural expectation, reinforced by subsequent work, that characteristics reducing participation costs should also improve conditional portfolio outcomes. We show that when participation involves delegating control to a technology, this alignment breaks down systematically. The fixed costs of discovery and the marginal costs of ceding decision authority respond to the same investor characteristics in opposite directions. This result arises because the canonical framework does not distinguish between entering a market and entrusting decisions to an algorithm. In standard participation models, the investor who enters retains full control over her portfolio; the act of participating does not require relinquishing decision authority. Robo-advising fundamentally alters this structure. Adoption requires ceding control, and the characteristics that facilitate entry including but not limitd to experience, wealth, sophistication are precisely those that make ceding control costly. This distinction becomes increasingly important as delegated technologies proliferate in household finance.

Third, the underdiversification opposite sign provides novel evidence for an awareness mechanism in which biased investors avoid corrective technology precisely because they underestimate the costs of their behavior. This contributes to the behavioural finance literature on the relationship between bias awareness and financial decision-making (Barber & Odean, 2001; Goetzmann & Kumar, 2008; Lusardi & Mitchell, 2014). The standard view holds that financial technology can serve as a corrective device, nudging investors toward better outcomes (Reher & Sokolinski, 2024; Rossi & Utkus, 2024). Our findings complicate this view. If the investors who would benefit most from algorithmic diversification are least likely to adopt voluntarily, then the corrective potential of FinTech is undermined by the very biases it seeks to remedy. Expanding access requires more than lowering fees or improving interfaces. It requires overcoming an awareness barrier that is most severe among the investors with the greatest need. This selection pattern has broader implications for the design of FinTech interventions. Policies that rely on voluntary adoption may systematically fail to reach the investors who stand to gain the most, suggesting a role for targeted nudges, default enrollment, or educational interventions that make bias costs salient before the adoption decision.

Fourth, the comparison with automated trading contributes to the literature on algorithm aversion (Dietvorst et al., 2015, 2018). Prior work has documented that individuals resist algorithmic recommendations across a range of domains, but has not disaggregated aversion by the degree of decision

authority transferred. We show that investors readily automate execution while resisting delegation of portfolio decisions. Algorithm aversion does not operate uniformly across all forms of financial automation. It is concentrated at the point where decision authority transfers from the investor to the algorithm. This finding implies that models of FinTech adoption must disaggregate by the extent of delegation. Technologies that preserve user control, like automated trading, attract a broad and heterogeneous user base through convenience and low setup costs. Technologies that require ceding control, like robo-advising, attract a narrower but more committed user base through genuine preference for delegation. Extrapolating insights from execution automation to delegated advice, or vice versa, produces misleading predictions about demand, user composition, and the intensive margin of technology use.

The remainder of the paper proceeds as follows. Section 2 develops the conceptual framework. Section 3 presents data and methodology. Section 4 reports the main results on determinants of participation and delegation. Section 5 compares robo-advising with rule-based automation. Section 6 examines performance signals. Section 7 analyzes dynamic participation margins. Section 8 examines selection heterogeneity. Section 9 concludes.

2. Conceptual Framework

This section develops a simple economic framework that rationalizes the opposite signs between adoption and delegation. The model clarifies how fixed discovery costs, marginal delegation costs, and bias awareness interact to generate opposite-signed effects across margins. We distinguish between biases that respond to awareness updating, such as underdiversification, and biases that impose persistent costs regardless of awareness, such as limited attention.

2.1. Setup

Endowed with initial wealth of 1, An investor i in period t holds financial wealth on the platform (including self-directed mutual funds and robo-advised assets) with value W_{it}. The investor makes two decisions: (i) whether to adopt robo-advising, and (ii) conditional on adoption, what share $s_{it} \in [0, 1]$ of value W_{it} to delegate. Self-directed mutual fund options has shares of $1 - s_{it}$.

2.2. Preferences

Utility from robo-advising combines expected returns, de-biasing benefits, and control costs:

$$U_{it}^{\text{RA}}(s) = r_{it}^{\text{RA}} \cdot s_{it} + \beta_B B_{it} \cdot s_{it} - \beta_C \psi_{it} \cdot s_{it}^2, \tag{1}$$

where r_{it}^{RA} is expected return, $B_{it} \geq 0$ measures bias intensity (underdiversification, disposition effect, etc.), $\beta_B > 0$ captures algorithmic correction benefits, $\psi_{it} \geq 0$ measures preference for control, and $\beta_C > 0$ scales the quadratic control cost.

Utility from self-directed investing combines expected returns, skill returns, and bias costs:

$$U_{it}^{\text{Self}} = r_{it}^{\text{Self}} \cdot (1 - s_{it}) + \beta_S \cdot \text{Skill}_{it} \cdot (1 - s_{it}) - \lambda_{it} \omega B_{it} \cdot (1 - s_{it}) - \kappa A_{it} \cdot (1 - s_{it}), \tag{2}$$

where $\beta_S > 0$ captures returns to active skill, $\omega > 0$ is the true cost of biased behavior, $\lambda_{it} \in [0, 1]$ measures the investor's awareness of this cost, $A_{it} \geq 0$ measures limited attention, and $\kappa > 0$ captures the cost of inattention in self-directed investing.

The distinction between B_{it} and A_{it} is conceptually important. Underdiversification (a part of B_{it}) is a portfolio characteristic that robo-advising directly corrects through algorithmic diversification. Limited attention (A_{it}) is a cognitive constraint that limits the investor's capacity to evaluate, adopt, and manage any investment strategy. Robo-advising does not cure inattention; it merely shifts the object of attention from portfolio management to robo-advisor monitoring.

2.3. The Awareness Mechanism

The key assumption for correctable biases is that biased investors underestimate the costs of their behavior:

$$\lambda_{it} = \lambda_0 - \lambda_1 B_{it}, \qquad \lambda_1 > 0. \tag{3}$$

When $\lambda_1 > 0$, awareness decreases in bias intensity: the most underdiversified investors are least aware of diversification benefits. This captures a regularity in which the severity of a bias correlates with unawareness of its costs. Goetzmann and Kumar (2008) show underdiversified investors exhibit overconfidence about their portfolio choices; Odean (1998) documents that investors with disposition effects believe they time sales well. Adoption updates awareness for correctable biases. Investors who try robo-advising observe disciplined diversified management directly:

$$\lambda_{it}^{\text{post}} = \lambda_{it} + \Delta\lambda, \qquad \Delta\lambda > 0. \tag{4}$$

Limited attention operates through a different channel. Inattentive investors do not underestimate the costs of inattention in the same way that underdiversified investors underestimate concentration costs. Rather, inattention directly impedes the cognitive processes required for adoption and ongoing engagement. We model this as a direct cost that scales with attention demands:

$$C_{it}^{A} = \theta_F A_{it} + \theta_M A_{it} \cdot s, \tag{5}$$

where $\theta_F > 0$ captures the attention cost of evaluating and adopting robo-advising, and $\theta_M > 0$ captures the attention cost of monitoring and adjusting delegation intensity. Unlike underdiversification, limited attention imposes costs at both margins, because adoption does not reduce attentional capacity and may even increase investors' attentional burden if they decide to hold RA and self-directed mutual funds at the same time after robo-advising usage.

2.4. Cost Structure

Adoption requires overcoming the fixed costs of discovery

$$C_{it}^{F} = c_0 - \boldsymbol{\alpha}' \mathbf{X}_{it}^{F} + \theta_F A_{it}, \tag{6}$$

where $c_0 > 0$ is a baseline fixed cost, $\mathbf{X}_{it}^F$ is a vector of investor characteristics that affect discovery costs, $\boldsymbol{\alpha}$ is a conformable vector of coefficients, and $\theta_F > 0$ captures the attention cost of evaluating a new financial product.

Characteristics that plausibly reduce fixed costs ($\alpha_j > 0$) include wealth, which proxies for financial sophistication and exposure to financial services marketing; age, which correlates with accumulated financial literacy; trading experience, which reduces information asymmetry about investment products; platform tenure, which provides interface familiarity and lowers search costs; and prior robo-advisor experience on other platforms, which provides direct familiarity with algorithmic advice. Some characteristics may increase fixed costs ($\alpha_j < 0$). Female investors, for example, may face higher discovery costs due to differential marketing exposure or lower baseline confidence in algorithmic tools (Barber & Odean, 2001; Croson & Gneezy, 2009). Limited attention increases fixed costs because evaluating a new financial product requires cognitive engagement that inattentive investors find costly.

Delegation imposes marginal costs that scale with the share delegated (Calvet et al., 2007)

$$C_{it}^M(s) = \left(\gamma_0 + \boldsymbol{\gamma}'\mathbf{X}_{it}^M + \theta_M A_{it}\right) \cdot s, \tag{7}$$

where $\gamma_0 \geq 0$ is a baseline marginal cost, $\mathbf{X}_{it}^M$ is a vector of investor characteristics that affect the cost of delegating control, $\boldsymbol{\gamma}$ is a conformable vector of coefficients, and $\theta_M > 0$ captures the attention cost of monitoring and adjusting delegation. Characteristics that plausibly increase marginal costs ($\gamma_j > 0$) include trading experience, because accumulated human capital in portfolio management has higher opportunity cost when ceded to an algorithm (Lusardi & Mitchell, 2014); age, because established investment routines and habits are psychologically costly to disrupt (Samuelson & Zeckhauser, 1988); and liquidity preference, because delegation reduces flexibility to respond to changing circumstances or liquidity needs (Brunnermeier & Pedersen, 2009). Inattentive investors face higher marginal costs because monitoring robo-advisor performance and adjusting allocations over time requires ongoing cognitive engagement that they are reluctant to provide. Some characteristics may reduce marginal costs ($\gamma_j < 0$). Risk-tolerant investors, for example, may find delegation less costly because they are more comfortable with the uncertainty inherent in ceding control.

2.5. Optimal Decisions and the Signs of Marginal Effects

The investor adopts if the expected utility from optimal delegation exceeds fixed costs

$$\text{Adopt}_{it} = 1 \quad \Leftrightarrow \quad V(s_{it}^*) - C_{it}^F > \eta_{it}, \tag{8}$$

where $V(s_{it}^*)$ is indirect utility evaluated at the optimal delegation share and η_{it} is an unobserved taste shock. Conditional on adoption, the optimal delegation share balances the benefits of algorithmic management against the costs of ceding control

$$s_{it}^* = \frac{\Delta r_{it} + \beta_B B_{it} + \lambda_{it}^{\text{post}} \omega B_{it} - \beta_S \text{Skill}_{it} - \gamma_0 - \boldsymbol{\gamma}'\mathbf{X}_{it}^M - \theta_M A_{it}}{2\beta_C \psi_{it}}, \tag{9}$$

where $\Delta r_{it} = r_{it}^{\text{RA}} - r_{it}^{\text{Self}}$ is the expected return differential between robo-advised and self-directed portfolios.

The model generates opposite signs across adoption and delegation margins through different channels. For biases such as underdiversification that robo-advising directly remedies, the adoption effect depends on the balance between algorithmic correction benefits and the unawareness barrier

$$\frac{\partial \Pr(\text{Adopt} = 1)}{\partial B_{it}} \propto \beta_B - \lambda_1 \omega. \tag{10}$$

If unawareness dominates ($\lambda_1 \omega > \beta_B$), biased investors are less likely to adopt despite having more to gain from algorithmic correction. Post-adoption, awareness updates and the delegation effect becomes

$$\frac{\partial s^*}{\partial B_{it}} = \frac{\beta_B + \lambda_1 \omega}{2\beta_C \psi} > 0. \tag{11}$$

The sign is unambiguously positive because both algorithmic correction benefits and updated awareness reinforce delegation. This generates the central prediction for correctable biases. Higher bias reduces adoption probability but increases delegation conditional on adoption.

Other characteristics can reduce fixed costs while increasing marginal costs, generating sign reversals through a different channel. Let X_j denote such a characteristic with $\alpha_j > 0$ in the fixed cost equation and $\gamma_j > 0$ in the marginal cost equation. The comparative statics are

$$\frac{\partial \Pr(\text{Adopt} = 1)}{\partial X_j} \propto \alpha_j > 0, \tag{12}$$

$$\frac{\partial s^*}{\partial X_j} = -\frac{\gamma_j}{2\beta_C \psi} < 0. \tag{13}$$

Trading experience and age are examples of characteristics that plausibly operate through this channel. Experienced investors find it easy to evaluate robo-advising because they possess financial literacy and familiarity with investment products. Yet, conditional on adoption, they delegate less because the human capital they have accumulated in portfolio management has higher opportunity cost when ceded. Older investors similarly benefit from accumulated financial knowledge that reduces discovery costs, but established investment routines make delegation psychologically costly.

Some characteristics may affect fixed costs without entering the marginal cost function. Let X_k denote such a characteristic with $\alpha_k > 0$ in the fixed cost equation and $\gamma_k = 0$ in the marginal cost equation. The comparative statics are

$$\frac{\partial \Pr(\text{Adopt} = 1)}{\partial X_k} \propto \alpha_k > 0, \qquad \frac{\partial s^*}{\partial X_k} = 0. \tag{14}$$

Tenure is an example. Investors with longer tenure face lower discovery costs due to greater platform or FinTech sophistication and marketing exposure, but tenure does not affect the tradeoff between control and delegation conditional on adoption. Tenure facilitates trial without affecting conditional commitment. For cognitive constraints such as limited attention that robo-advising does not remedy, both margins reflect the same underlying cost.

$$\frac{\partial \Pr(\text{Adopt} = 1)}{\partial A_{it}} \propto -\theta_F < 0, \tag{15}$$

$$\frac{\partial s^*}{\partial A_{it}} = -\frac{\theta_M}{2\beta_C \psi} < 0. \tag{16}$$

Limited attention reduces adoption because evaluating robo-advising is cognitively costly. It reduces delegation because monitoring and adjusting robo-advised portfolios requires ongoing attention. Unlike underdiversification, there is no awareness updating channel. Adoption does not make inattentive investors more attentive. The absence of opposite signs across the margins for cognitive constraints distinguishes them from correctable biases and provides a falsification test for the awareness mechanism.

2.6. Empirical Implications

The framework generates several testable predictions that distinguish alternative mechanisms. The first prediction concerns characteristics that reduce fixed costs but increase marginal costs. Variables such as trading experience and age should increase adoption but decrease delegation. A pure discovery-cost model without marginal cost heterogeneity would predict same-signed effects at both margins. The second prediction concerns correctable biases. The awareness mechanism predicts that underdiversification reduces adoption but increases delegation. A model without awareness updating ($\Delta\lambda = 0$) would predict that bias reduces both margins or affects neither. The third prediction concerns cognitive constraints. Limited attention should reduce both adoption and delegation because inattention imposes costs at both margins without awareness updating. Observing opposite signs for limited attention would contradict the model and suggest that the distinction between correctable biases and cognitive constraints is incorrect. The fourth prediction concerns extensive-margin-only variables. Characteristics such as tenure that affect discovery costs but not the control-delegation tradeoff should predict adoption but not conditional delegation intensity. The fifth prediction concerns selection on unobservables. If unobserved match quality affects both decisions, the inverse Mills ratio coefficient should be positive. Investors who adopt despite observable barriers have revealed a higher unobserved affinity for algorithmic advice and should delegate more intensively.

The contrast between underdiversification and limited attention provides the key test of the awareness mechanism. A pure fixed-cost model would predict that both variables reduce adoption with no conditional effect on delegation. In such a model, biased investors face higher perceived costs of entry because their existing behavior is further from what algorithmic management would prescribe, creating a larger gap between current practice and the required adjustment. Once an investor pays the fixed cost and adopts, however, the bias has no further role because delegation intensity is determined entirely by preferences over risk, return, and control that are independent of the bias that initially deterred adoption. Both underdiversification and limited attention would therefore reduce adoption but have no systematic relationship with delegation conditional on entry. A model with uniform awareness updating predicts that both variables generate sign reversals, because if adoption universally corrects investor biases then any bias that initially discourages adoption should increase delegation once the

investor experiences the platform and revises beliefs about its value. Under uniform updating, both concentrated investors and inattentive investors would discover upon adoption that algorithmic management addresses their respective limitations, leading both groups to delegate more intensively than their adoption propensities would suggest. The selective awareness model developed here predicts a sign reversal for underdiversification (correctable through algorithmic diversification) but not for limited attention (a cognitive constraint that adoption does not remedy). The differential sign pattern uniquely identifies the awareness mechanism. Figure 1 illustrates these predictions. Panel (a) plots adoption probability as a joint function of bias intensity (B) and awareness (λ). When awareness is high, increased bias raises adoption because investors recognize the value of algorithmic correction. When awareness is low, increased bias reduces adoption because investors underestimate the costs their biases impose. Panel (b) plots the delegation share conditional on adoption. Post-adoption, increased bias always raises delegation because adoption updates awareness to $\lambda^{post} = \lambda + \Delta\lambda$. The model predicts sign reversals precisely when pre-adoption awareness is low but post-adoption awareness is high.

3. Data and Methodology

3.1. Institutional Background

Alipay is China's largest mobile payment and wealth management platform, operated by Ant Group. The platform integrates payments, commerce, and financial services within a unified interface. Users access savings products, mutual fund distribution, and wealth management tools alongside everyday transactions without establishing separate account relationships.

This integrated design is central to our empirical setting. Alipay combines fund distribution, portfolio holding, and performance display within a single user experience. Investors browse funds, execute transactions, and monitor positions with minimal operational frictions. Holdings and performance are displayed in standardized formats, making outcomes salient and comparable across products. The platform supports joint holding of multiple asset categories: liquid money-market balances (i.e., Yu'e Bao, named as Baby Assets in the paper; investors can use the fund to consume and trade on financial assets directly on Alipay), self-directed mutual fund positions, and delegated robo-advised portfolios. Investors reallocate between these options without opening separate accounts or transferring funds across platforms. This facilitates repeated interactions: investors can enter, scale back, exit, and re-enter delegated products while continuing to trade self-directed funds.

BangNiTou ("Help You Invest") is a digital fund investment advisory service jointly founded by Ant Group and Vanguard. The service provides fully delegated mutual fund portfolio management: after collecting suitability information, BangNiTou recommends a diversified portfolio and implements transactions and periodic rebalancing on the investor's behalf. A defining feature is deep integration within Alipay. Investors hold BangNiTou portfolios alongside self-directed investments within the same account environment. Switching between delegated and self-directed modes does not require leaving the platform. Adoption is not irreversible: investors can enter, scale, exit, and re-enter delegated management while maintaining self-directed positions. This design yields several advantages for empirical analysis. First, we observe both delegated and self-directed behavior for the same in-

vestor in the same environment, enabling direct measurement of behavioural biases without relying on external accounts or surveys. Second, low switching costs ensure that observed participation decisions reflect preferences rather than mechanical frictions. Third, dynamic usage is naturally supported, making re-participation an empirically meaningful investigation. BangNiTou serves several million users and manages assets at a meaningful scale within Alipay. The service charges annual management fees of 0.20–0.50% of delegated asset value, comparable to global robo-advisors. Portfolio construction follows modern portfolio theory, with diversified allocations across equity and fixed-income mutual funds tailored to investor risk profiles. Automatic rebalancing occurs when allocations drift beyond pre-specified thresholds.

The integrated platform provides a natural laboratory for studying delegation demand that has few parallels in other markets.[1] Alipay operates as a one-stop financial ecosystem for Chinese retail investors, combining payments, savings, insurance, and investment within a single application. With over one billion users and dominant penetration across income and geographic strata, the platform serves as the primary investment channel for the vast majority of its active investors. This makes it reasonable to treat observed behaviour as approximating overall individual decisions rather than a selected fragment of activity conducted alongside unobserved holdings elsewhere. Retail investment in the United States and Europe is fragmented across brokerages, banks, or standalone robo-advisors, and no single platform commands comparable dominance over household financial activity. Three features of this setting are especially valuable for identification. First, delegated robo portfolios and self-directed fund trading coexist within the same account, eliminating confounds from external holdings. Second, common liquidity infrastructure and performance display ensure that switching costs between delegated and self-directed investing are negligible and comparative information is salient. Third, observable dynamic participation at a monthly frequency, including entry, exit, and re-entry, enables identification of distinct participation margins.

The low fixed costs of adoption may lead to higher experimentation rates than standalone platforms, and salient performance comparisons may amplify learning effects. However, the fundamental economic forces we study, like opposite signs reflecting tensions between exposure and commitment, adverse selection reflecting preferences for control, should operate in any setting where delegation is partial and reversible. Online Appendix A1.1 provides detailed comparisons with global robo-advisors and discusses external validity.

A natural concern is that investors may hold mutual fund positions on platforms other than Alipay, in which case the delegation share we observe understates the investor's total portfolio and may not reflect the true proportion of wealth allocated to robo-advising. We cannot rule this out entirely, but several features of the institutional setting make single-platform concentration substantially more likely than in Western markets. First, Alipay is the single largest mutual fund distribution channel in China, larger than any individual bank. In the first ranking of fund distributors published by the Asset Management Association of China (AMAC) in 2021, Ant's fund sales arm held 890.1 billion yuan ($138.2 billion) in outstanding non-money-market mutual funds, ahead of China Merchants Bank (707.9 billion yuan) and the Industrial and Commercial Bank of China (Galbraith & Zhou, 2021). By mid-2022, online platforms accounted for 39 percent of third-party fund distribution, up from 32 per-

[1] If interested, we provide more details on the institutional background in the Online Appendix A1.1.

cent just one year earlier, with the three largest platforms, like Ant Fund Sales, East Money's Tiantian, and Tencent's TengAn, collectively responsible for roughly 70 percent of all online distribution assets (The Asset, 2022). Ant Fortune, the wealth management platform within Alipay, served 500 million active users and managed 4 trillion RMB (US$605 billion) in assets by May 2022 (Singapore Management University, 2023).

Second, the super-app ecosystem creates strong lock-in that discourages multi-platform investing. Alipay integrates payments, shopping, transportation, insurance, lending, and investing into a single application. A CPP Investments report documents that, unlike Western consumers who use different apps for different functions, Chinese consumers tend to consolidate their digital activities within a single super-app (CPP Investments, 2023). An S&P Global survey of 1,000 Chinese internet users found that 95 percent use Alipay and 94 percent use both Alipay and WeChat, with mobile payments reported as the dominant activity across these platforms (S&P Global Market Intelligence, 2020). Hong et al. (2025) describe how Alipay embeds mutual fund distribution alongside everyday services such as ride-hailing and food delivery, making fund investment "as easy as other aspects of everyday life." According to the AMAC, 71 percent of retail investors purchase mutual funds through mobile apps (cited in Hong et al., 2025), and Cerulli Associates reports that nearly 90 percent of individual mutual fund investors invest online (Acosta, 2020). The leading digital platforms, including Ant Fortune, each carry over 6,000 funds—more than 70 percent of all public mutual funds available in the market and double the number offered by banks (Au, 2021). An investor who uses Alipay for payments, bill settlement, and money market savings faces minimal incremental friction when investing in mutual funds or robo-advisory products on the same platform, but substantial switching costs if she were to open and fund a separate account on a competing platform for the same purpose. Third, even if some investors do hold positions elsewhere, this would bias our delegation share estimates *downward*, working against finding the opposite-sign patterns that are the paper's central result. The underdiversification opposite sign, for instance, would be attenuated rather than amplified by unobserved outside holdings, making our estimates conservative.

We construct a panel of 100,000 investors observed monthly from September 2020 to September 2024 (49 months, 4.9 million investor-month observations). The sample is drawn from active mutual fund investors satisfying three criteria: (i) registration on Alipay prior to September 2020, which avoids contamination from users whose registration and investment decisions are jointly determined during the sample period; (ii) age between 18 and 80, focusing on adults while excluding ages at which platform registration is implausible or likely reflects data errors; and (iii) at least one consumption record, mutual fund holding, purchase, and sale during the sample period, ensuring active portfolio decision-makers rather than dormant accounts.

We stratify the sample to ensure sufficient variation for studying both the extensive margin (whether to adopt) and the intensive margin (how much to delegate, conditional on adoption). The sample comprises 70,000 investors who adopted BangNiTou at least once and 30,000 who actively traded mutual funds but never adopted. This stratified design follows standard practice in studies of rare events where the outcome of interest has low base rates (Manski & Lerman, 1977).

For each investor-month, we observe granular portfolio positions and transactions across multiple asset categories within the Alipay ecosystem: mutual funds (self-directed), BangNiTou robo-

advised portfolios, Yu'e Bao money-market holdings, gold holdings, and other financial products. This comprehensive view of the Alipay balance sheet is central to our analysis because it allows us to construct portfolio shares, compute value-weighted returns separately for self-directed and robo-advised sleeves, and measure liquidity preferences and safe-asset demand. We supplement portfolio data with demographic characteristics (age, gender, province of residence), platform-usage variables (registration tenure, engagement with other robo-advisory products), and survey-based risk preference measured on an eight-level scale.

We merge investor data with fund-level characteristics from Morningstar Direct, including monthly closing prices, Morningstar category classifications, and fund-level return histories spanning the full observation period. Morningstar categories provide a granular classification system that groups funds by asset class, geographic focus, and investment style, allowing us to construct category-matched performance benchmarks that control for systematic differences in fund objectives and risk profiles (Calvet et al., 2007). This merged dataset combines granular investor behavior with comprehensive fund characteristics, enabling us to separately identify investor skill, fund selection, and market performance in our analysis of robo-advisor adoption decisions.

The extensive margin is captured by an adoption indicator $d_{it} = 1$ if investor i holds a positive robo-advised position in month t. The intensive margin is the delegation share:

$$s_{it} = \frac{\text{RA Value}_{it}}{\text{RA Value}_{it} + \text{Fund Value}_{it}}, \quad \text{if } d_{it} = 1. \tag{17}$$

Then, we construct a comprehensive set of investor-level covariates capturing demographics, preferences, experience, skill, and behavioural biases. The first category comprises demographics and preferences. We observe total financial assets held on Alipay, which proxies for wealth and financial engagement. Age and gender capture life-cycle and demographic heterogeneity in delegation demand. Province fixed effects control for regional variation in financial development and digital literacy. Survey-based risk preference, measured on an eight-level scale, captures stated preferences over portfolio risk. We also include Baby Assets, the value of money-market holdings in Yu'e Bao, which proxies for liquidity preference and precautionary saving motives.

The second category captures platform engagement. Registration tenure measures the number of months since the investor joined Alipay, proxying for platform familiarity and trust accumulation. We also construct a Combined RA Dummy indicating whether the investor uses any other robo-advisory product available on Alipay, capturing persistent heterogeneity in willingness to delegate portfolio decisions.

The third category measures investment experience and skill. Fund trading experience is the cumulative number of months the investor has maintained active mutual fund holdings, capturing learning and familiarity with portfolio management; a longer track record proxies for accumulated knowledge that may reduce the marginal value of delegating to a robo-advisor. Following Grinblatt and Keloharju (2009), we decompose portfolio performance into two orthogonal components: selection skill, measured as value-weighted excess returns relative to Morningstar category benchmarks, and timing skill, measured as returns attributable to within-month trading decisions rather than passive holding. Decomposing skill in this way matters because the two components reflect fundamentally different

abilities: selection skill captures the capacity to identify superior funds within an asset class, while timing skill captures the ability to exploit short-term return predictability through active reallocation, and conflating them into a single performance measure would obscure which dimension drives delegation decisions. Crucially, both measures isolate skill from risk-taking and trading intensity, ensuring that high returns driven by leverage or excessive turnover are not mistakenly attributed to genuine ability. Construction details are in Online Appendix A1.3.

The fourth category comprises behavioural biases documented in the household finance literature. We focus on this particular set of biases because each has been shown to generate measurable welfare losses in retail investment contexts, and together they span distinct psychological mechanisms, including limited cognitive resources, loss aversion, probability weighting, and overconfidence, ensuring that our behavioural measures capture heterogeneity across multiple, largely orthogonal dimensions of investor psychology rather than a single underlying trait.

Following Goetzmann and Kumar (2008), we measure underdiversification using portfolio concentration and return comovement; underdiversification is among the most prevalent and costly mistakes in retail portfolios (Blume & Friend, 1975), making it a natural first-order predictor of delegation demand. Following Barber and Odean (2008), we construct a limited attention measure based on trading activity in attention-grabbing funds; investors with binding attention constraints are precisely those most likely to benefit from delegating the information-processing burden to an algorithm (Peng & Xiong, 2006). Following Odean (1998), we measure the disposition effect as the differential propensity to realize gains versus losses; this bias produces systematic deviations from optimal rebalancing (Shefrin & Statman, 1985) that rule-based advising is well positioned to correct. We further construct measures of extrapolation bias (return-chasing behavior), gambling bias (preference for lottery-like funds), and speculative turnover (profit-taking trades associated with overconfidence), which jointly capture investors' tendencies to extrapolate past returns (Barberis et al., 2015), seek skewed payoffs at the expense of diversification (Kumar, 2009), and overtrade in ways that erode net returns (Barber & Odean, 2000). These measures capture behavioural heterogeneity that may shape delegation demand in opposing ways: investors exhibiting stronger biases may benefit more from robo-advising (D'Acunto et al., 2019), but may simultaneously be less aware of their own biases and thus less likely to seek algorithmic guidance (Tversky & Kahneman, 1974). See Online Appendix A1.3 for detailed definitions.

Besides individual's returns on their mutual fund portfolio and robo-advised holdings, we also construct robo-advising return gaps (RRG) as log gross-return differences:

$$\mathrm{RRG}_{it} = \ln(1 + r_{it}^{\mathrm{Fund}}) - \ln(1 + r_{it}^{\mathrm{RA}}). \tag{18}$$

We decompose RRG into positive ($\mathrm{RRG}^{+} = \max\{\mathrm{RRG}, 0\}$) and negative ($\mathrm{RRG}^{-} = \min\{\mathrm{RRG}, 0\}$) components to test for asymmetric responses. We construct both market-level and individual-level RRG measures. The market-level RRG measure uses the return on an averaged robo-advisor benchmark portfolio that is identical across all investors, capturing aggregate algorithmic performance that is exogenous to individual allocation decisions. The individual-level RRG measure uses each investor's own realized robo-advisor return, which reflects the interaction between the common algorithmic strategy and the investor's specific delegation timing and intensity. Comparing the two allows us to

distinguish whether investors respond to the general performance signal available to all participants or to the personalized outcome shaped by their own delegation choices.

3.2. Empirical Strategy

The intensive margin is observed only for adopters, creating a selection problem. If unobservables affecting adoption (e.g., trust in algorithms) correlate with unobservables affecting delegation (e.g., confidence in robo performance), naive estimation on the selected sample yields biased coefficients. We address this using Heckman two-step estimation (Heckman, 1979). The selection equation is a probit for adoption:

$$\Pr(d_{it} = 1 \mid \mathbf{Z}_{it-1}) = \Phi(\mathbf{Z}'_{it-1}\boldsymbol{\gamma}), \tag{19}$$

where $\mathbf{Z}_{it-1}$ includes predetermined investor characteristics. The outcome equation is:

$$s_{it} = \mathbf{X}'_{it-1}\boldsymbol{\beta} + \delta \cdot \text{IMR}_{it} + \varepsilon_{it}, \quad \text{if } d_{it} = 1, \tag{20}$$

where IMR is the inverse Mills ratio from the first stage. A significant δ indicates selection on unobservables; $\delta > 0$ implies that unobservables increasing adoption also increase delegation.

Platform tenure serves as the exclusion restriction in the Heckman selection model. Investors who have maintained an Alipay account for longer are more likely to encounter the robo-advisory feature through routine platform use, promotional notifications, and accumulated familiarity with the application interface. Longer tenure reduces the discovery and information costs associated with learning that robo-advising exists and understanding how it functions, thereby increasing the probability of adoption. However, conditional on having adopted, there is no clear economic reason why the length of time an investor has held an Alipay account should influence the share of investable wealth delegated to algorithmic management. The delegation decision reflects preferences over risk, control, diversification, and opportunity costs of ceding decision authority, none of which are mechanically related to how long the investor has been on the platform. This satisfies the exclusion restriction requirement that the instrument affects selection into the sample but is excludable from the outcome equation. The argument is analogous to geographic proximity instruments used in the mutual fund literature, where distance to a fund family headquarters predicts participation but does not directly affect portfolio allocation conditional on investing. Platform tenure operates through a similar channel, lowering the cost of awareness and access without altering the economic tradeoffs that govern delegation intensity.

To allow for time-varying relationships while estimating stable cross-sectional effects, we implement the Fama–MacBeth estimation procedure (Fama & MacBeth, 1973). Specifically, we estimate the Heckman selection model separately for each of the 49 months in our sample and report the time-series averages of the monthly slope coefficients:

$$\bar{\boldsymbol{\beta}} = \frac{1}{T}\sum_{t=1}^{T} \hat{\boldsymbol{\beta}}_t. \tag{21}$$

This approach preserves cross-sectional variation in investor characteristics, many of which are time-invariant or highly persistent, while allowing coefficients to vary flexibly across periods. A conven-

tional panel specification with investor fixed effects would absorb time-invariant heterogeneity and therefore prevent identification of key demographic and behavioural variables central to our analysis. In addition, fixed-effects models primarily exploit within-investor variation over time and thus address a different economic question, namely how changes within an individual relate to changes in portfolio allocation. Our objective is instead to characterize systematic cross-sectional differences in allocation across investors. The Fama–MacBeth framework identifies relationships from cross-sectional dispersion each month and bases statistical inference on the time-series variation of the estimated coefficients, thereby accommodating arbitrary cross-sectional dependence within periods.

Standard errors are computed from time-series variation in monthly estimates, with Newey–West corrections for autocorrelation (Newey & West, 1987). This approach accommodates time-varying coefficient stability without imposing restrictive functional forms.

All right-hand-side variables are lagged one month to ensure predetermined timing.[2] We include province fixed effects in both equations. Continuous variables are standardized to a mean of zero and unit standard deviation within each month. We apply month-specific calibration weights to restore population representativeness in estimation.[3] Tables in the Online Appendix A1.6 report unweighted estimates using the raw stratified sample as a robustness check. This study was remotely conducted on the Ant Open Research Laboratory in an Ant Group Environment. All data was sampled and desensitized, and was analyzed on the Ant Open Research Laboratory.[4] The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis and individual observations are invisible. The main regression variables include basic variables, investment variables, and robo-advising variables. Tables 1 reports summary statistics of all variables we applied.[5]

A note on the evaluation of marginal effects is warranted given our sampling design. Our estimation sample has a 32.1% adoption rate, substantially higher than the population rate of approximately 1%. We weight observations to restore population representativeness in coefficient estimation. However, we report marginal effects evaluated at the sample adoption rate ($\phi(z_0) = 0.357$) rather than the population rate ($\phi(z_0) = 0.027$) for consistency with the reported regression tables. This choice affects only the absolute magnitudes of adoption effects, not the sign patterns or relative magnitudes that are central to our analysis. At the population adoption rate, all adoption marginal effects would be approximately 13 times smaller ($0.027/0.357 \approx 0.075$). The delegation effects, opposite signs, hypothesis tests, and all comparative conclusions are invariant to this choice.

[2]The number of monthly cross-sections varies across specifications. The baseline uses T=48 months (one month is lost to lagging). Specifications including behavioural biases use T=46 due to the requirement of sufficient within-month variation for bias construction. The automated trading specification uses T=28 months, reflecting the shorter availability in the sample of that product.

[3]Monthly adoption incidence in the population is approximately 1%. For each month t, observations with $\text{RA}_{it} = 1$ receive weight $p^{\text{pop}}/p_t^{\text{samp}}$, while observations with $\text{RA}_{it} = 0$ receive weight $(1 - p^{\text{pop}})/(1 - p_t^{\text{samp}})$, where $p^{\text{pop}} = 0.01$ and p_t^{samp} is the sample adoption rate in month t. Weights are normalized to a unit mean within each month. See Online Appendix A1.2 for details.

[4]https://www.deor.org.cn/labstore/laboratory

[5]If interested, we provide more details on the variable constructions and methodology applications in the Online Appendix A1.2 to A1.4.

4. Determinants of Participation and Delegation

We now turn to the central empirical question: what drives robo-advisor adoption, and do these same forces govern how intensively adopters delegate? Our evidence reveals systematic differences between the extensive and intensive margins, with many investor characteristics exhibiting opposite signs across the two decisions. We present three sets of results in sequence: demographics and account characteristics, experience and skills, and behavioural biases. We then test the sign patterns against the three alternative models developed in Section 2 and summarize the decomposition of adoption and delegation effects from three specifications in Table 2 to Table 4.

The adoption equation uses case-control weights; we evaluate marginal effects at the empirical adoption rate ($p_0 = 0.321$, implying $\phi(z_0) = 0.357$). The outcome equation standardizes RA_share; we report effects in raw units using $\mathbb{E}[\text{RA_share} \mid \text{RA} = 1] = 10.17\%$ and SD $= 15.83\%$.

4.1. Demographics, Account Characteristics, and the Adoption-Allocation Gap

Table 2 reveals sharp distinctions between the determinants of adoption and those of delegation. Many covariates exhibit statistically significant effects on both margins, yet frequently with different signs or magnitudes. This adoption-allocation disconnection constitutes the central empirical pattern of the paper. Wealth strongly predicts adoption ($\hat{\gamma} = 0.113$, $t = 8.29$), raising the probability by 4.0 percentage points per standard deviation. Conditional on adoption, however, wealth exerts no significant effect on delegation. The implication is that wealth operates almost entirely on the extensive margin, consistent with proportional discovery costs that facilitate entry without reshaping marginal allocation decisions (Calvet et al., 2007). Age exhibits a opposite sign. Older investors are more likely to adopt ($\hat{\gamma} = 0.049$, $t = 4.04$), with the effect corresponding to a 1.8 percentage point increase in probability. Yet conditional on adoption, older investors delegate less ($\hat{\beta} = -0.020$, $t = -3.13$), a reduction of 0.32 percentage points or 3.1% of the mean. Age thus encourages experimentation while tempering the depth of commitment. Gender differences are statistically strong but economically modest. Female investors are less likely to adopt ($\hat{\gamma} = -0.102$, $t = -9.10$), a gap of 3.6 percentage points. They also delegate less conditional on adoption ($\hat{\beta} = -0.026$, $t = -5.76$), though the magnitude remains small at 0.41 percentage points, or 4.0% of the mean. The gender gap operates primarily through participation rather than through large conditional portfolio shifts.

Risk tolerance affects both margins without opposite sign. Risk-tolerant investors are more likely to adopt ($\hat{\gamma} = 0.109$, $t = 6.29$), an increase of 3.9 percentage points, and they delegate more conditional on adoption ($\hat{\beta} = 0.020$, $t = 3.88$), by 0.32 percentage points or 3.1% of the mean. Robo-advising is evidently not used solely as a low-risk default. Risk-tolerant investors both adopt and scale up their delegation. Liquidity preference reduces both margins. Higher Baby Assets lower adoption ($\hat{\gamma} = -0.043$, $t = -14.05$) by 1.5 percentage points and reduce delegation conditional on adoption ($\hat{\beta} = -0.023$, $t = -7.21$) by 0.36 percentage points, or 3.6% of the mean. A preference for liquid, low-commitment holdings competes directly with delegation to automated strategies.

Prior robo-advisor experience with other providers on the platform ranks among the strongest adoption predictors ($\hat{\gamma} = 0.719$, $t = 32.76$), raising the probability by 26 percentage points. The delegation effect, while positive, is modest ($\hat{\beta} = 0.029$, $t = 2.71$), amounting to 0.46 percentage

points or 4.5% of the mean. Familiarity lowers entry barriers substantially but does not translate into large delegation. Selection correction proves quantitatively important. The inverse Mills ratio is positive and significant ($\hat{\delta} = 0.242$, $t = 6.85$), implying that unobserved factors favoring adoption also raise delegation by 3.8 percentage points, or 37% of the mean. This result validates the Heckman framework. Adoption and delegation are governed by distinct mechanisms, and investors who adopt despite unobservable barriers delegate substantially more.

4.2. Experience, Sophistication, and the Limits of Delegation

Table 3 examines how investment experience and skill shape the adoption-allocation gap. Fund trading experience exhibits a pronounced opposite sign. Experience strongly predicts adoption ($\hat{\gamma} = 0.385$, $t = 3.61$), raising the probability by 13.7 percentage points. Conditional on adoption, however, experience substantially reduces delegation ($\hat{\beta} = -0.326$, $t = -1.87$), by 5.2 percentage points or fully 51% of the mean. Experienced investors try robo-advising readily but delegate sparingly. Their reluctance to cede accumulated human capital to algorithms is evident in the estimates.

Selection skill modestly increases adoption ($\hat{\gamma} = 0.012$, $t = 2.20$), raising the probability by 0.4 percentage points, but exerts no significant effect on delegation. Investors skilled at fund selection do not systematically adjust their delegation intensity. Timing skill offers a different picture. It does not predict adoption, yet conditional on adopting, skilled timers delegate more ($\hat{\beta} = 0.009$, $t = 2.32$), by 0.14 percentage points or 1.4% of the mean. These investors appear to view robo-advising as complementary to, rather than a substitute for, their own market timing. The inverse Mills ratio remains significant ($\hat{\delta} = 0.183$, $t = 4.90$), corresponding to a 2.9 percentage point increase in delegation, or 28% of the mean.

Taken together, the experience results sharpen the adoption-allocation gap. Sophistication increases willingness to experiment but not the depth of commitment. Experienced investors treat robo-advising as a supplementary tool rather than a replacement for active management.

4.3. Behavioural Biases, Awareness, and the Boundaries of Commitment

The opposite sign patterns documented in Table 4 are most pronounced for behavioural biases, and Figure 2 visualizes the key patterns. Behavioural biases are systematic, predictable deviations from rational decision-making that lead investors to make suboptimal portfolio choices. Unlike random errors, these biases are persistent and rooted in well-documented psychological mechanisms, making them particularly relevant for understanding when and why investors choose to delegate portfolio decisions to an algorithm.

Panels (a) and (b) plot adoption probability and delegation share against underdiversification, which measures the degree to which an investor holds an overly concentrated portfolio instead of spreading risk across many funds. The slopes present opposite signs. Underdiversified investors are significantly less likely to adopt, yet those who do adopt delegate substantially more. This pattern aligns with the awareness mechanism developed in Section 2. Underdiversified investors underestimate the costs of concentration and therefore undervalue algorithmic diversification. Those who adopt, perhaps through chance exposure or salient losses, update their beliefs and commit intensively.

Table 4 examines how behavioural biases shape participation and delegation more broadly. Panels (c) and (d) of Figure 2 display the corresponding relationships for limited attention, which captures whether investors allocate sufficient cognitive resources to monitoring and evaluating their portfolios. The pattern differs sharply. Limited attention reduces both adoption probability and delegation intensity, with no opposite sign. This contrast validates the theoretical distinction between correctable biases and persistent cognitive constraints. Underdiversification is correctable because the act of adoption itself triggers belief updating. Limited attention persists because adoption cannot expand attentional capacity. The investor who delegates because she lacks time to monitor positions remains limitedly attentive after delegation.

Underdiversification exhibits the sharpest opposite sign of any variable in the analysis. Concentrated investors are less likely to adopt ($\hat{\gamma} = -0.256$, $t = -21.57$), a reduction of 9.1 percentage points. Yet conditional on adoption, underdiversification increases delegation ($\hat{\beta} = 0.027$, $t = 7.40$) by 0.43 percentage points, or 4.2% of the mean. This reversal is consistent with the awareness mechanism in Section 2. Underdiversified investors underestimate the costs of concentration and therefore avoid robo-advising. Those who adopt update their beliefs and use robo-advising as a commitment device against their own bias.

Limited attention operates primarily as an entry friction. The attention bias reduces adoption ($\hat{\gamma} = -0.048$, $t = -7.80$) by 1.7 percentage points. Its delegation effect is negative but small ($\hat{\beta} = -0.005$, $t = -3.19$), reducing delegation by only 0.08 percentage points, or 0.8% of the mean. Extrapolation bias, the tendency to assume that recent fund returns will continue into the future, does not affect adoption but modestly reduces delegation ($\hat{\beta} = -0.005$, $t = -4.26$), by 0.08 percentage points or 0.8% of the mean. Investors who chase recent performance pull back from delegation at the margin.

Speculative turnover, which captures excessive trading driven by overconfidence in one's ability to time the market, exerts extreme effects on both margins. It strongly reduces adoption ($\hat{\gamma} = -14.98$, $t = -3.63$), effectively driving predicted adoption to zero among highly speculative investors.[6] Conditional on adoption, speculative turnover reduces delegation ($\hat{\beta} = -3.60$, $t = -3.02$) by 57 percentage points, representing near-complete crowd-out. A control-oriented or entertainment-motivated trading style is fundamentally incompatible with algorithmic delegation. The inverse Mills ratio remains large and significant ($\hat{\delta} = 0.241$, $t = 6.71$), corresponding to 37% of the mean.

The behavioural results reinforce the paper's central finding. Biases rooted in avoidance and inattention impede entry. Biases associated with speculation and the desire for control sharply limit delegation depth. Investors may well experiment with new technology yet resist relinquishing autonomy, particularly when the act of trading itself provides utility beyond expected returns. Our main specifications apply calibration weights to restore population representativeness given the stratified sampling design that oversamples robo-advisor adopters. Online Appendix A1.6 reports unweighted estimates using the raw stratified sample. All sign patterns are preserved and coefficient magnitudes shift only modestly. The substantive conclusions do not depend on the weighting procedure.

[6] The coefficient magnitude implies near-corner solutions rather than marginal adjustments.

4.4. Testing Alternative Models and Summary of Sign Patterns

The contrast between underdiversification and limited attention provides a joint test of the awareness mechanism against competing explanations. Table 5 summarizes the predictions of three models alongside our empirical estimates using the behavioural bias specification (Table 4) which includes the full set of controls.

A pure fixed cost model with homogeneous awareness predicts that both biases affect adoption through discovery costs but have no effect on delegation conditional on adoption. The jointly significant delegation coefficients for underdiversification ($\hat{\beta} = +0.027$, $t = 7.40$) and limited attention ($\hat{\beta} = -0.005$, $t = -3.19$) reject this model. The Wald test of $\beta_{\text{underdiv}} = \beta_{\text{attention}} = 0$ yields $\chi^2(2) = 64.9$ ($p < 0.001$). A uniform awareness model in which all biases trigger belief updating upon adoption predicts opposite signs for both underdiversification and limited attention. The significantly negative delegation coefficient for limited attention rejects this model. The one-sided test of $H_0 : \beta_{\text{attention}} \geq 0$ yields $p = 0.0007$.

Only the selective awareness model generates the observed pattern: a opposite sign for underdiversification (a correctable bias where adoption reveals diversification benefits and updates beliefs) and same-signed negative effects for limited attention (a cognitive constraint that adoption does not remedy). Both conditions are satisfied: the test $\beta_{\text{underdiv}} > 0$ yields $p < 0.0001$, and the test $\beta_{\text{attention}} < 0$ yields $p = 0.0007$.

Figure 3 summarizes the marginal effects of all key variables across both margins, and Figure 4 maps each variable into the sign-pattern space implied by the framework. Three variables exhibit opposite signs across the adoption and delegation margins. Experience and age operate through the fixed versus marginal cost channel: more experienced and older investors face lower discovery costs but higher opportunity costs of ceding human capital and disrupting established routines. The experience reversal is marginally significant for the delegation margin ($t = -1.87$, $p = 0.06$), while age achieves conventional significance at both margins. Underdiversification operates through the awareness mechanism: concentrated investors face unawareness barriers to adoption but delegate more once they observe algorithmic diversification.

Wealth operates exclusively at the extensive margin with no conditional effect on delegation, consistent with the theoretical prediction that wealth reduces fixed discovery costs without affecting the marginal tradeoff between control and delegation. In Figure 4, wealth lies directly on the horizontal axis. Limited attention, gender, risk tolerance, and prior robo-advisory experience produce reinforcing effects that work in the same direction at both margins. The reinforcing pattern for limited attention is theoretically important: it confirms that inattention is a cognitive constraint rather than a correctable bias, since adoption does not remedy the underlying constraint and both margins reflect the same cost.

The prevalence of opposite signs carries a methodological implication for the broader literature. A reduced-form regression of total robo-advised wealth on investor characteristics would estimate attenuated coefficients as opposing forces partially offset. Studies that do not separate the two margins risk concluding that investor characteristics have limited effects on robo-advisor use when in fact the effects are substantial but heterogeneous across margins. The two-margin decomposition is not merely a refinement; it reveals economic structure that single-equation approaches obscure.

5. Robo-Advising versus Rule-Based Automation

A central question for interpreting our findings is whether the documented patterns reflect attitudes toward financial automation in general or toward robo-advising in particular. If investors exhibit similar opposite signs and selection patterns for any automated financial tool, our results speak to broad automation preference or aversion. If the patterns are confined to robo-advising, they speak instead to the particular economics of delegating portfolio decisions to algorithms. This section exploits within-platform variation to distinguish these two interpretations.

5.1. Institutional Comparison

The Alipay platform offers two distinct automated investment features. *Robo-advising* (BangNiTou) constructs and rebalances diversified mutual fund portfolios on the investor's behalf. Investors specify risk preferences and investment horizons, and the algorithm selects funds, determines allocations, and executes rebalancing. Decision authority over portfolio composition transfers entirely to the algorithm. *Automated mutual fund trading*, by contrast, allows investors to establish rule-based periodic purchases or subscriptions to self-selected funds. The investor chooses which funds to purchase and specifies contribution amounts and frequencies. The platform then executes these pre-specified instructions automatically. Decision authority over fund selection remains entirely with the investor.

The two features thus occupy opposite ends of the delegation spectrum. Robo-advising requires ceding control over what to invest in. Automated trading cedes control only over when to execute decisions the investor has already made. Both involve financial automation, but only robo-advising involves algorithmic portfolio management. This contrast enables a clean test. If our documented patterns, including the opposite signs, the awareness-driven selection, and the intensive-margin commitment, reflect general automation aversion, they should appear symmetrically for both products. If they instead reflect the specific economics of delegating portfolio decisions, they should appear only for robo-advising.

5.2. Adoption and Allocation Patterns

Table 6 reports Heckman estimates for automated trading, paralleling the robo-advising specifications in Section 4. Table 7 summarizes the key contrasts.

Extensive-margin adoption rates are remarkably similar in our sample, with 32.9% for automated trading versus 32.1% for robo-advising. At the adoption margin, the two products attract comparable shares of the investor population. This similarity suggests that general factors such as platform familiarity, comfort with digital finance, and willingness to engage with automated tools drive extensive-margin decisions for both products.

Intensive-margin allocations diverge dramatically. Mean allocation to automated trading is 3.7% (SD = 6.47%), compared with 10.17% (SD = 15.83%) for robo-advising.[7] Investors allocate nearly three times more wealth to robo-advising than to rule-based execution. This gap is surprising. One might expect investors to commit more readily to a tool that preserves their decision authority. Instead,

[7]Sample moments for automated trading are $p_0 = 0.329$ and $\phi(z_0) = 0.362$. For robo-advising the corresponding values are $p_0 = 0.321$ and $\phi(z_0) = 0.357$.

the pattern suggests that investors who adopt robo-advising exhibit stronger commitment than those who adopt automated trading. We test this hypothesis through the selection analysis below.

Risk tolerance increases both robo-advising adoption ($\hat{\gamma} = 0.109$, $t = 6.29$) and delegation ($\hat{\beta} = 0.020$, $t = 3.88$). For automated trading, risk preference also increases adoption ($\hat{\gamma} = 0.069$, $t = 5.25$) but has no effect on allocation intensity ($\hat{\beta} = -0.004$, $t = -1.49$). Risk-tolerant investors scale up algorithmic delegation but not rule-based automation.

This asymmetry suggests that risk preference proxies for willingness to cede decision authority, not merely for comfort with financial technology. Risk-tolerant investors may be more confident that algorithmic decisions will produce acceptable outcomes, or they may place lower value on retaining personal control. Either interpretation implies that risk preference operates through the delegation channel specifically.

Gender has no significant effect on automated trading adoption ($\hat{\gamma} = 0.010$, $t = 0.74$) or allocation ($\hat{\beta} = 0.014$, $t = 0.83$). This stands in sharp contrast with robo-advising, where female investors are less likely to adopt ($\hat{\gamma} = -0.102$, $t = -9.10$) and delegate less conditional on adoption ($\hat{\beta} = -0.026$, $t = -5.76$). The gender gap in robo-advising therefore reflects skepticism about algorithmic portfolio management specifically, not aversion to financial automation in general. Female investors adopt automated trading at rates indistinguishable from those of male investors. The barrier lies in delegating decision authority to algorithms, consistent with evidence that women exhibit lower confidence in algorithmic judgment (Logg et al., 2019) or stronger preferences for maintaining control over consequential financial decisions.

Timing skill reduces automated trading adoption ($\hat{\gamma} = -0.004$, $t = -11.88$) but has no significant effect on robo-advising adoption ($\hat{\gamma} = 0.002$, $t = 0.32$). The differential makes economic sense. Automated trading eliminates the ability to time contributions, directly undermining the value of timing skill. Skilled timers avoid it precisely because it negates their comparative advantage. Robo-advising, by contrast, does not preclude timing. Investors can adjust their robo-advised allocation at any time, adding or withdrawing funds in response to market conditions. The algorithm manages within-portfolio allocation, but the investor retains control over total allocation to the robo-portfolio. Skilled timers do not avoid robo-advising because it preserves scope for timing at the portfolio level.

The underdiversification results provide the sharpest test of our awareness mechanism. For robo-advising, underdiversification reduces adoption ($\hat{\gamma} = -0.256$, $t = -21.57$) but increases delegation conditional on adoption ($\hat{\beta} = 0.027$, $t = 7.40$). This opposite sign is the signature of awareness updating. Underdiversified investors avoid robo-advising because they underestimate the costs of concentration, but those who adopt discover the benefits of diversification firsthand and delegate substantially. For automated trading, underdiversification also reduces adoption ($\hat{\gamma} = -0.715$, $t = -9.49$), yet the opposite sign fails to appear. The delegation effect is insignificant ($\hat{\beta} = 0.011$, $t = 0.47$). Underdiversified investors who adopt automated trading do not delegate more than their diversified counterparts.

Why does the awareness mechanism operate for robo-advising but not for automated trading? The answer lies in what each product reveals upon adoption. Robo-advised portfolios are diversified by construction. Investors who adopt observe diversification benefits directly through portfolio composition and realized return patterns. Automated trading, by contrast, merely executes contributions to

funds the investor has already selected. If the investor chose concentrated funds, automated trading perpetuates rather than corrects that concentration. The differential opposite sign thus identifies the mechanism with precision. Awareness updating requires that adoption reveal the benefits of correction. Robo-advising satisfies this condition. Automated trading does not.

The inverse Mills ratio delivers the most striking contrast between the two products. For robo-advising, the IMR is positive and highly significant ($\hat{\delta} = 0.242$, $t = 6.85$), implying that unobservable factors increasing adoption propensity also increase delegation intensity. Selection raises delegation by 37% of the mean adopter allocation. Marginal robo-advising adopters, those who adopt despite observable barriers, reveal strong unobserved commitment and delegate substantially. For automated trading, the IMR is statistically insignificant ($\hat{\delta} = 0.154$, $t = 1.21$). Selection on unobservables is absent. Marginal automated trading adopters do not exhibit greater commitment than infra-marginal adopters. This selection reversal crystallises the fundamental distinction between products. Robo-advising attracts committed delegators. Investors who adopt have revealed a preference for algorithmic management, and those who overcome barriers delegate intensively. Automated trading attracts experimenters and convenience-seekers. Adoption reflects low setup costs and ease of use, not a strong preference for rule-based execution.

5.3. Summary and Interpretation

Table 7 summarizes the comparison. Three patterns stand out.

First, the underdiversification opposite sign is specific to robo-advising. This constitutes our key test of the awareness mechanism. The reversal operates when adoption reveals diversification benefits and vanishes when it does not. The differential pattern identifies awareness updating as the operative channel and rules out alternative explanations that would apply symmetrically to both products.

Second, risk preference and gender affect robo-advising but not automated trading. These variables operate through willingness to cede decision authority. Investors who are risk-tolerant or male show greater willingness to delegate portfolio decisions to algorithms, yet they exhibit no differential propensity toward rule-based execution that preserves their authority.

Third, selection operates for robo-advising but not for automated trading. The positive IMR for robo-advising implies that adopters who overcome barriers are committed delegators. The null IMR for automated trading implies that its adopters form a more heterogeneous group that includes experimenters and convenience-seekers. This divergence in selection explains why robo-advising adopters allocate nearly three times more than automated trading adopters despite virtually identical adoption rates. Robo-advising selects for commitment. Automated trading does not.

These patterns carry important implications for understanding fintech adoption. Not all automation is equivalent. Technologies that preserve user control, like automated trading, exhibit weak or absent selection, with adoption driven by convenience and experimentation. Technologies that require ceding control, like robo-advising, exhibit strong positive selection, with adoption driven by genuine preference for delegation.

Conflating these distinct forms obscures economically meaningful heterogeneity. The determinants of trying a technology may look similar across automation types; platform familiarity, age, and experience predict adoption of both products. But the determinants of relying on a technology *inten-*

sively diverge sharply as a function of delegation depth. Models of technology adoption must therefore distinguish control-preserving from control-relinquishing features. Extrapolating insights from execution automation to delegated advice, or vice versa, produces misleading predictions about demand, user composition, and the intensive margin of technology use.

6. Performance Signals and Feedback in Delegation

This section examines whether market or realized performance serves as a feedback signal that affects the intensity of delegation among robo-advisor adopters. Conceptually, this mechanism differs from the adoption decision itself. Entry into robo-advising reflects experimentation costs, awareness, and trust in automation, whereas delegation intensity may respond endogenously to perceived performance quality after adoption has already occurred. Investors who have adopted robo-advising may adjust the fraction of their portfolios delegated to the algorithm in response to recent returns.

6.1. Fund Returns

Table 8 augments the baseline specification with lagged fund portfolio returns. Across all horizons, fund returns do not significantly predict robo-advising adoption in the selection equation. More importantly for the intensive margin, none of the fund return measures enter the outcome equation with statistical significance. The estimated coefficients are economically close to zero.

This absence of feedback indicates that investors do not treat fluctuations in their self-directed fund portfolios as informative signals for adjusting how much wealth they delegate to automation. Conditional on adoption, delegation decisions appear largely insulated from performance variation in conventional fund investments.

6.2. Robo-Advisor Returns

Table 9 turns to realized performance of the robo-advising strategy itself. In contrast to fund returns, short-horizon robo-advisor returns generate statistically significant feedback on delegation intensity.

At the one-month horizon, lagged robo-advisor returns enter the outcome equation with a negative and statistically significant coefficient ($\beta = -0.006, t = -1.96$). The economic magnitude is modest, implying a reduction in the delegated share on the order of one percent of the mean adopter allocation.[8] A similar pattern emerges at the three-month horizon. The cumulative three-month return also enters with a negative and statistically significant coefficient of comparable magnitude ($\beta = -0.006$, $t = -2.00$), implying nearly identical economic effects.[9]

By contrast, six-month cumulative returns are statistically insignificant. Performance feedback is concentrated at short horizons and dissipates over longer windows. Notably, none of the robo-advisor return measures significantly predict adoption in the selection equation. Performance therefore affects the intensive margin of delegation but does not discipline entry into robo-advising.

[8]Using SD$(RA_share \mid RA = 1) = 0.1583$, the implied raw change is $-0.006 \times 0.1583 \approx -0.00095$, or -0.10 percentage points, corresponding to roughly 0.9 percent of the mean adopter allocation of 10.17 percent.

[9]The implied raw change is again approximately -0.10 percentage points, corresponding to about 1 percent of the mean adopter allocation.

6.3. Fund and Robo-Advisor Returns Jointly

Table 10 includes fund and robo-advisor return signals simultaneously. The joint specification confirms the asymmetry documented above. Fund returns remain statistically insignificant in both the adoption and delegation equations. Robo-advisor returns continue to affect delegation intensity only at short horizons and with economically modest magnitudes. The stability of coefficients on demographic characteristics, preferences, and experience across specifications is reassuring. It indicates that performance feedback operates as a small overlay on persistent cross-sectional heterogeneity rather than as a primary driver of delegation behavior.

6.4. Relative Return Gaps

Tables 11 and 12 examine relative return gaps as alternative performance and regret signals. In symmetric specifications, neither market-level nor individual-level relative return gaps significantly predict robo-advising adoption. In the outcome equation, coefficients are statistically insignificant across all horizons, indicating no systematic adjustment of delegation intensity when relative gains and losses are pooled together.

6.5. Asymmetric Signals

Allowing for asymmetric responses yields sharper insights. Table 13 shows that positiv market-level relative return gaps enter the adoption equation with statistical significance. A one-month positive market relative return gap significantly reduces robo-advising adoption ($\alpha = -0.919$, $t = -2.50$), indicating that unusually favorable relative market performance is associated with a sharp decline in the propensity to begin using robo-advising.[10]

The economic interpretation is intuitive. Strong positive relative market outcomes increase investors' perceived ability or confidence in self-directed investing, thereby reducing the perceived value of algorithmic advice. Favorable market conditions discourage entry into robo-advising by reinforcing beliefs in personal skill or control.

Asymmetric individual-level relative return gaps primarily affect the intensive margin. Positive individual relative return gaps at the one-month horizon significantly reduce the delegated share among adopters ($\beta = -0.013$, $t = -1.86$). Although the magnitude is economically modest, the direction is consistent with the adoption results. Unusually favorable relative outcomes lead investors to modestly scale back their delegation.[11]

Taken together, these asymmetric effects point toward a confidence or control channel rather than a loss-aversion channel. Positive relative performance, whether measured at the market or individual level, reduces reliance on automation. It either deters adoption altogether or slightly contracts delegated capital among existing adopters. Negative relative outcomes, by contrast, do not generate

[10] For standardized regressors in a probit model, the marginal effect at baseline adoption probability p_0 is $\phi(z_0)\alpha$, where $z_0 = \Phi^{-1}(p_0)$. With $p_0 = 0.321$, this mapping implies a reduction in adoption probability on the order of 33 percentage points. Given the bounded nature of probabilities and the large coefficient magnitude, this calculation should be interpreted as indicating near-complete suppression of predicted adoption at high positive relative return gap values rather than as a literal linear probability change.

[11] The implied raw change is $-0.013 \times 0.1583 \approx -0.00206$, or -0.21 percentage points, corresponding to roughly 2 percent of the mean adopter allocation.

symmetric increases in delegation. This asymmetry implies that robo-advising is not primarily used as an insurance device against poor performance. It functions instead as a substitute for self-directed decision-making, one that becomes less attractive when investors experience recent success.

6.6. Interpretation

Performance signals generate statistically detectable but economically modest feedback in delegation intensity. The clearest effects arise from short-horizon robo-advisor returns and asymmetric positive relative performance signals, both of which induce small retrenchments in delegated capital. These magnitudes pale in comparison with the large cross-sectional differences in delegation driven by investor characteristics such as experience, liquidity preferences, and speculative behavior documented in earlier sections.

These findings complement the household finance literature emphasizing inertia and heterogeneity in participation decisions (Campbell, 2006). We show that realized performance does not discipline entry into automation but induces limited adjustment on the intensive margin. Delegation therefore reflects stable preferences for control, attention, and experimentation rather than continuous re-optimization in response to noisy short-run returns. Performance matters, but only at the margin, and it does not overturn the central adoption-allocation gap identified in Section 4.

7. Dynamic Participation

This section disaggregates participation into three distinct margins, each reflecting different economic forces and selection mechanisms. First-time adoption, continuation, and re-entry represent fundamentally different decisions, and pooling them in the general specification may obscure important heterogeneity.

7.1. Sample Definitions

We partition the sample based on each investor's adoption history.

- *First use* comprises investor-months in which $RA_{i\tau} = 0$ for all $\tau < t$. The observed rate is 1.43%.
- *Continuation* comprises investor-months in which $RA_{it-1} = 1$. The observed rate is 30.44%.
- *Re-entry* comprises investor-months in which the investor has used robo-advising in the past, did not use it last month, and resumes use this month. The observed rate is 0.20%.

Mean delegation differs markedly across margins, registering 10.83% for first-use adopters, 10.07% for continuing users, and 15.26% for re-entrants. The substantially higher delegation among re-entrants suggests positive selection on commitment.[12]

7.2. Key Patterns Across Margins

Table 18 summarizes the main coefficient patterns. We highlight the most striking findings in Table 18.

[12]Sample moments are as follows. General sample: $p_0 = 0.321$, $\phi(z_0) = 0.357$. First-use: $p_0 = 0.0143$, $\phi(z_0) = 0.037$. Continuation: $p_0 = 0.3044$, $\phi(z_0) = 0.350$. Re-entry: $p_0 = 0.0020$, $\phi(z_0) = 0.006$.

In the general specification, wealth increases adoption by 4.0 percentage points with no delegation effect. Disaggregation reveals that this average masks opposing patterns. Wealth has no effect on first-time adoption but strongly predicts continuation (1.7 pp). Wealthy first-time users and re-entrants delegate cautiously, with reductions of 7.5% and 13.3% of their respective margin means.[13] This pattern is consistent with sophistication-induced hedging. Wealthy investors who experiment with robo-advising limit their initial commitment, but those who find the experience satisfactory persist.

The general participation gender gap of -3.6 percentage points in adoption and -4.0% in delegation conflates opposing forces. Female investors face large barriers to first-time use (-0.41 pp) and re-entry (-0.10 pp). Yet female investors who do adopt are *more* likely to continue (2.7 pp) and delegate *more* than their male counterparts (2.6% of the continuation mean).[14] The implication is that female investors either commit fully or exit permanently. Those who overcome initial barriers reveal strong match quality and persist at higher rates than men. The general participation results, by averaging across these opposing forces, understate both the entry friction and the persistence advantage. The inverse Mills ratio reveals striking variation across margins.

- At first use, $\hat{\delta} = 0.042$ and is statistically insignificant. No selection on unobservables operates at initial entry.
- In the general specification, $\hat{\delta} = 0.242$, corresponding to 37% of the mean. Moderate selection is present.
- In continuation, $\hat{\delta} = 2.177$, corresponding to 339% of the mean. Selection is very strong.
- At re-entry, $\hat{\delta} = 0.214$ and is again insignificant. Re-entrants form a heterogeneous, unselected pool.

Selection on unobserved match quality does not operate at the moment of first adoption. It accumulates dramatically through persistence. Continuing users have revealed strong affinity for algorithmic delegation through their sustained participation. Re-entrants, by contrast, constitute a mixed group that includes investors who exited following negative experiences alongside those whose departures were driven by idiosyncratic circumstances. The age opposite sign documented in the general specification, with positive adoption effects and negative delegation effects, also operates for first-time users. In continuation, age strongly predicts persistence (2.4 pp) but the delegation effect vanishes.[15] Older continuing users have sorted into stable allocations.

The re-entry margin tells a different story. Older investors are less likely to return (-0.04 pp), reversing the sign observed at other margins. Older investors who exit tend not to come back, suggesting that their departures reflect deliberate decisions rather than transient experimentation.

Liquidity preference, measured by Baby Assets, reduces general participation by 1.5 percentage points in adoption and 3.5% in delegation. Yet liquidity increases first-use probability (0.09 pp) and re-entry probability.[16] Liquidity-seeking investors are willing to experiment precisely because they face low switching costs and can exit at minimal cost.

Among continuing users, liquidity has no adoption effect but crowds out delegation (-3.1% of the continuation mean). The competition between liquid savings vehicles and delegated investment

[13] First-use delegation effect: $0.050 \times 0.1633/0.1083 \approx 0.075$. Re-entry: $0.095 \times 0.2140/0.1526 \approx 0.133$.
[14] Continuation effects: adoption, $0.350 \times 0.077 \approx 0.027$; delegation, $0.017 \times 0.1568/0.1007 \approx 0.026$.
[15] Continuation: $0.350 \times 0.068 \approx 0.024$.
[16] First-use effect: $0.037 \times 0.024 \approx 0.0009$.

reasserts itself once the experimentation phase has passed.

7.3. Summary

Four patterns emerge from the disaggregation. First, discovery costs facilitate continuation more than experimentation. Wealth and age show stronger adoption effects in continuation than in first-use, indicating that the resources and patience needed to sustain engagement matter more than those needed to initiate it. Second, selection accumulates through experience. The inverse Mills ratio grows from zero at first use, to a moderate level in the general specification, to a very large magnitude in continuation. Sorting on match quality builds over time as investors learn whether algorithmic delegation suits their preferences. Third, gender effects bifurcate in ways that the general specification cannot capture. Female investors face substantial entry barriers, but those who overcome them persist at higher rates and delegate more intensively. The pooled results conflate these opposing forces and obscure the underlying selection dynamics. Fourth, re-entry is governed by idiosyncratic rather than systematic factors. Age reduces re-entry, unlike other margins, and platform tenure has no effect. Re-entry appears driven by investor-specific circumstances that resist explanation by the covariates shaping other participation margins.[17]

8. Unobserved Heterogeneity and Delegation Intensity

The inverse Mills ratio coefficient is positive and statistically significant across all main specifications, implying that unobserved factors increasing adoption propensity also increase delegation intensity conditional on adoption. Among investors with identical observable characteristics, those who adopt have revealed stronger unobserved affinity for algorithmic advice. This affinity may reflect latent trust in automated systems, openness to relinquishing control, or recognition of one's own behavioural limitations. Whatever its source, this unobserved affinity manifests in greater delegation among adopters who overcame observable barriers to entry.

The magnitude is economically substantial. Selection raises delegation by approximately 37 percent of mean adopter allocation, an effect comparable to moving from the 25th to 75th percentile of fund trading experience. Marginal adopters are not reluctant experimenters who delegate tentatively. They are committed users whose observable characteristics understated their true demand for algorithmic delegation. The selection coefficient varies systematically across investor subgroups. Among younger investors, the coefficient is large and precisely estimated, implying strong positive sorting on unobserved match quality. Among older investors, the coefficient is small and inconsistently signed. Among less wealthy investors, selection is statistically insignificant. Among wealthy investors, selection turns negative, suggesting that wealthy marginal adopters are experimenters rather than committed users. For young and less wealthy investors, adopting robo-advice reveals genuine demand for delegation. For older and wealthier investors, adoption may reflect curiosity or low-cost diversification of advisory relationships. Selection also accumulates through experience. The coefficient is insignificant at first use, moderate in general participation, and very large among continuing users. Sorting on

[17] If interested, we provide the unweighted regression results in the Online Appendix A1.6.

match quality builds over time as investors learn whether robo-advising suits their preferences. Early adoption reveals little about unobserved commitment. Sustained use reveals much.

These patterns carry implications for interpreting platform metrics. Adoption statistics that count users without weighting by delegation intensity overstate the reach of robo-advising among older and wealthier investors. An investor who maintains a token position while concentrating wealth in self-directed accounts appears equivalent to one who delegates comprehensively. The selection analysis reveals that these investors differ not only in observed allocation but in unobserved commitment to the technology.

9. Conclusion

This paper addresses a central puzzle in the robo-advisor adoption literature: why do studies report contradictory findings about who adopts automated investment advice? We argue these contradictions reflect empirical conflation rather than genuine differences across settings. Most studies collapse two distinct decisions: whether to use robo-advice (extensive margin) and how much to delegate conditional on use (intensive margin), into a single outcome variable. Because these margins are governed by different economic forces, the same investor characteristic can exhibit opposite effects depending on which dimension dominates observed variation.

Using 49 months of panel data covering 100,000 investors on Alipay's BangNiTou platform, we document systematic opposite signs across margins. Wealth, age, and investment experience increase adoption but reduce delegation conditional on adoption, a pattern consistent with sophistication enabling experimentation while limiting commitment. Under-diversification reduces adoption yet increases delegation among adopters. We interpret this finding through an awareness mechanism whereby biased investors underestimate the costs of their behavior, though we acknowledge that alternative explanations, including heterogeneous treatment effects and selection on unobserved wealth constraints, cannot be fully ruled out with our identification strategy. Comparing robo-advising with automated trading, which preserves decision authority over fund selection, provides our cleanest test. The opposite signs and positive selection we document appear for robo-advising but not for automated trading, suggesting these patterns reflect the delegation of decision authority specifically rather than financial automation generally. This within-platform comparison controls for many potential confounds, though differences in user bases and product characteristics may still play a role.

Our findings carry three main implications, each subject to important caveats. First, for the adoption literature, understanding fintech usage may require distinguishing margins and phases. The inconsistencies documented across prior studies could reflect compositional variation in the mix of first-time adopters, continuous users, and re-entrants. However, institutional differences across platforms and markets may also contribute to cross-study variation in ways our single-platform analysis cannot address. Second, for platform design, our results suggest that exposure and discovery costs are important determinants of adoption. Wealth and tenure predict trial in our setting, potentially because they correlate with marketing exposure and accumulated platform trust. The gender patterns we document with women facing larger adoption barriers but exhibiting stronger persistence conditional on adoption, suggesting that efforts to close adoption gaps might productively focus on initial discovery. We

caution, however, that these patterns may be specific to integrated super-app environments with minimal switching costs. Third, for regulation and welfare, we find suggestive evidence that investors who might benefit most from automated diversification are less likely to adopt. If this pattern generalizes, voluntary adoption alone may not deliver welfare gains to those who need algorithmic guidance most, strengthening the case for targeted interventions. However, our analysis did not quantify the welfare effects, and the optimal policy response depends on factors beyond our data, including the quality of robo-advice and investors' outside options.

Several limitations qualify these conclusions and suggest directions for future research. Our setting is a single robo-advisor integrated within a Chinese super-app; the low switching costs and integrated interface may amplify the dynamic participation patterns we observe relative to standalone platforms in Western markets. External validity to settings like Betterment or Wealthfront, the two largest independent robo-advisors in the United States that operate as dedicated, standalone platforms serving clients through direct digital channels without the embedded ecosystem of a super-app, remains an open empirical question.

Our identification strategy relies on platform tenure as an exclusion restriction in the Heckman selection model. While tenure plausibly affects discovery costs, it may also correlate with unobserved preferences for delegation, potentially biasing our estimates of selection effects. Future work with cleaner identification, perhaps exploiting natural experiments in platform design or marketing, would strengthen causal interpretation. We observe holdings within Alipay but not investors' complete wealth, potentially overstating delegation intensity for investors who hold substantial assets elsewhere. More fundamentally, we cannot directly observe the "awareness updating" that our conceptual framework emphasizes. Direct evidence, for instance, whether adopters change their behavior in self-directed portfolios after experiencing robo-advising would more convincingly establish the mechanism. We leave this analysis for future work. Finally, our sample period (2020–2024) captures a relatively early stage of robo-advisory market development in China, whose financial and robo-advising market is still developing. As these services mature and investor familiarity grows, the patterns we document may evolve. Replication later across markets and time periods will be valuable for assessing generalizability.

Despite these limitations, we establish that robo-advisor demand is multi-dimensional. The decision to try robo-advice reflects exposure and experimentation costs; the decision of how much to delegate reflects preferences over control and perceptions of relative skill; the decision to persist or return reflects accumulated experience. Collapsing these decisions into a single adoption indicator obscures economically meaningful heterogeneity. The two-margin perspective we adopt offers a framework for interpreting FinTech adoption patterns and may help explain conflicting findings in this and related literature.

Figures

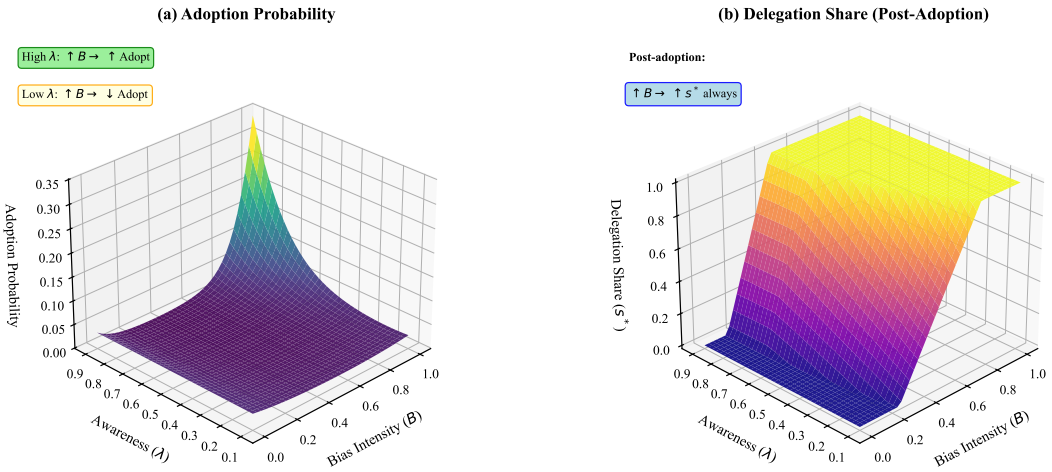


Figure 1: Theoretical Predictions of the Awareness Mechanism

Notes: This figure illustrates the theoretical predictions developed in Section 2. Panel (a) plots adoption probability as a function of bias intensity (B) and awareness (λ). When awareness is high, increased bias raises adoption because investors recognize the value of algorithmic correction. When awareness is low, increased bias reduces adoption because investors underestimate bias costs. The sign of the bias-adoption relationship depends on the investor's position along the awareness dimension. Panel (b) plots the delegation share conditional on adoption. Both surfaces are computed holding fixed all model parameters other than bias intensity and awareness. Post-adoption, increased bias always raises delegation because adoption updates awareness to $\lambda^{post} = \lambda + \Delta\lambda$. The model predicts opposite signs when pre-adoption awareness is low but post-adoption awareness is high.

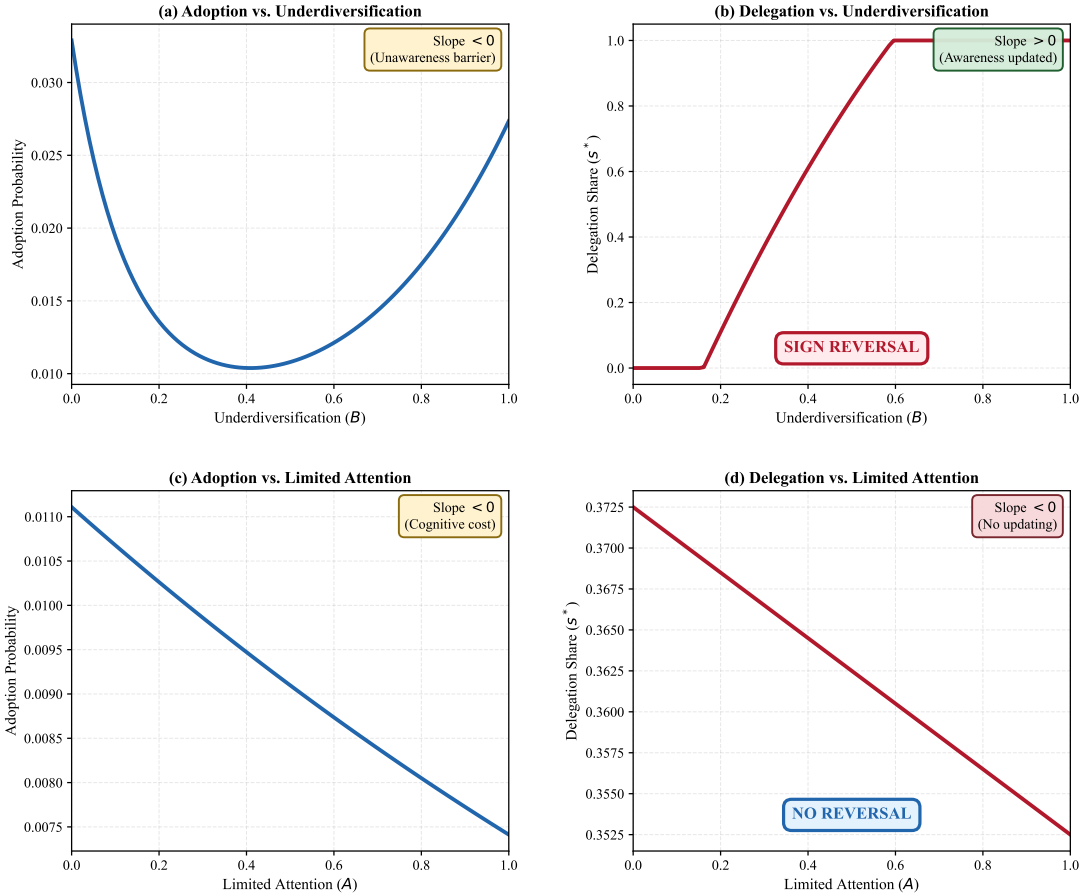


Figure 2: opposite signs for Behavioural Biases

Notes: This figure plots the relationship between behavioural biases and robo-advisor demand across the extensive and intensive margins. Panels (a) and (b) display adoption probability and delegation share as functions of underdiversification. Panels (c) and (d) display the same relationships for limited attention. Underdiversification exhibits a opposite sign: higher bias reduces adoption probability but increases delegation conditional on adoption. Limited attention exhibits no reversal: higher bias reduces both adoption and delegation. Slopes are estimated from the baseline Heckman selection model.

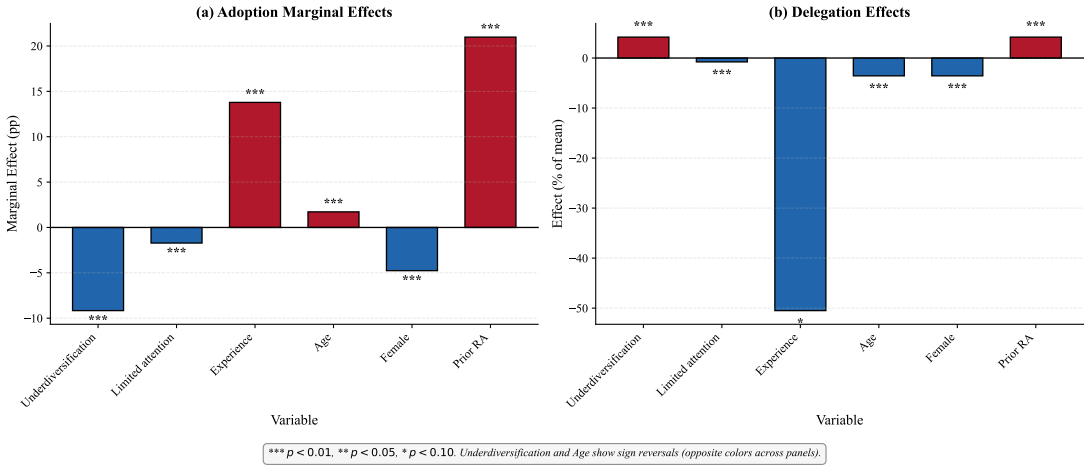


Figure 3: Marginal Effects on Adoption and Delegation

Notes: This figure summarizes the marginal effects of investor characteristics on robo-advisor adoption and delegation. Panel (a) reports marginal effects on adoption probability in percentage points per one-standard-deviation increase in each variable. Panel (b) reports effects on delegation intensity expressed as a percentage of mean adopter allocation. Red bars indicate positive effects; blue bars indicate negative effects. Variables displaying opposite colors across panels exhibit opposite signs. Estimates are from the baseline Heckman selection model with Fama-MacBeth aggregation. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

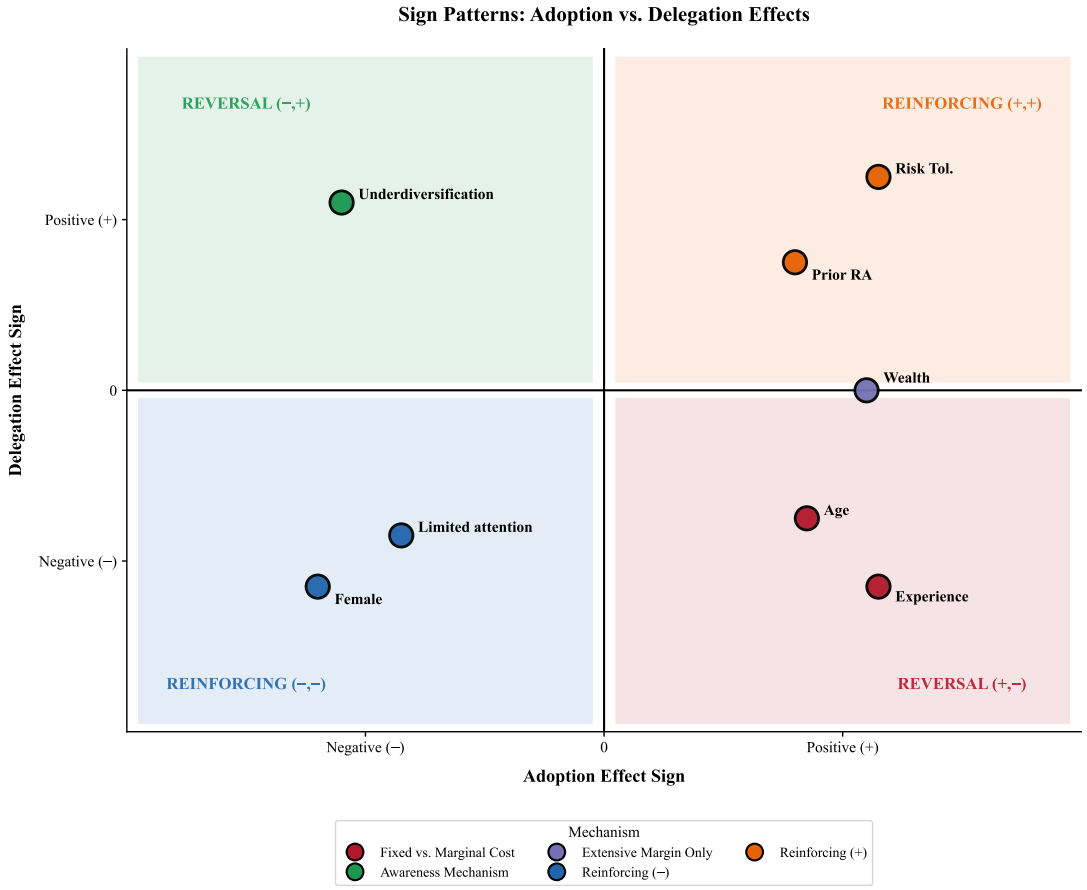


Figure 4: Sign Patterns Across Investor Characteristics

Notes: This figure maps investor characteristics according to their effects on adoption (horizontal axis) and delegation conditional on adoption (vertical axis). The upper-left quadrant (negative adoption, positive delegation) and lower-right quadrant (positive adoption, negative delegation) contain variables exhibiting opposite signs. The upper-right quadrant (positive, positive) and lower-left quadrant (negative, negative) contain variables with reinforcing effects. Colors indicate the theoretical mechanism consistent with each pattern: red denotes the fixed-versus-marginal-cost mechanism, green denotes the awareness mechanism, blue denotes extensive-margin-only effects, and orange denotes reinforcing effects. Wealth lies on the horizontal axis with no significant delegation effect, indicating that wealth operates purely through the extensive margin.

Tables

Table 1: Summary Statistics of Original Variables

Variable	Mean	Std. Dev.	Min	25%	50%	75%	Max
RA Variables							
ra_it	0.321	0.467	0.000	0.000	0.000	1.000	1.000
ra_share	0.097	0.158	1.008e-09	0.009	0.035	0.113	1.000
combined_ra_dummy_t	0.089	0.285	0.000	0.000	0.000	0.000	1.000
Demographic Variables							
user_id	59,000.500	40,648.910	1.000	25,007.750	50,005.000	75,002.250	130,000.000
age_as_of_20200930	32.536	9.791	1.800	25.000	30.000	37.000	80.000
gender	0.425	0.494	0.000	0.000	0.000	1.000	1.000
risk_preference	2.769	1.111	-2.000	2.000	3.000	4.000	5.000
registration_time	201,286.500	334,589.020	200,412.000	201,102.000	201,309.000	201,510.000	202,009.000
lengthreg	88.673	40.047	0.000	59.000	84.000	115.000	189.000
Asset Variables							
total_financial_assets_month_end	104,217.500	287,118.450	0.000	6,534.733	30,219.760	99,530.920	37,970,600.000
baby_assets_month_end	23,419.240	89,738.180	0.000	1,703.500	2,667.860	16,073.940	19,151,570.000
robo_advisor_assets_month_end	3,070.165	20,491.600	0.000	0.000	0.000	4,674.400	3,411,411.000
combined_advisor_assets_month_end	91,689.290	133,772.200	0.000	0.000	0.000	0.000	8,993,047.000
Behavioral Bias Variables							
underdiversification_score	0.536	0.236	0.000	0.332	0.515	0.734	1.000
limited attention_bias	0.448	0.420	0.000	0.000	0.385	1.000	1.000
disposition effect_ratio	55,649.930	452,386.300	0.000	0.124	1.099	16.906	192,329,600.000
extrapolation_bias	0.105	0.247	0.000	0.000	0.000	0.216	1.000
gambling_bias	0.012	0.086	0.000	0.000	0.000	0.000	1.000
anchoring_bias	0.487	0.437	0.000	0.000	0.475	1.000	1.000
total_turnover	0.306	3.997	0.000	0.000	0.116	0.574	412,216.500
speculative_turnover	0.278	1.807	0.000	0.000	0.000	0.000	351,258.300
Fund Experience Variables							
exp_ra_months	7.901	1.044	0.000	1.000	1.000	1.200	49.000
exp_fund_months	2.323	1.353	0.000	1.200	2.300	3.400	49.000
selection_score	-0.002	0.026	-0.704	-0.011	-0.001	0.006	1.329
timing_score_0_100	49.609	28.752	0.001	24.762	49.904	74.521	100.000
Fund Holdings Variables							
fund_total_holdings_value_month_end	76,514.830	219,354.400	0.000	3,571.565	19,001.210	68,785.960	37,789,640.000
n_funds	12.655	30.396	1.000	3.000	7.000	14.000	5,952.000
n_funds_using_avg	0.871	4.112	0.000	0.000	0.000	0.000	1,274.000
Fund Returns							
fund_vw_portfolio_return	-0.002	0.055	-0.900	-0.028	-1.192e-05	0.017	1.000
fund_vw_portfolio_return_lag1	-0.004	0.046	-0.900	-0.020	0.000	0.008	1.000
fund_vw_portfolio_return_prev3_cum	-0.010	0.077	-2.342	-0.045	0.000	0.013	1.475
fund_vw_portfolio_return_prev6_cum	-0.019	0.093	-4.442	-0.060	0.000	0.015	1.485
Market Returns							
ra_market_return	0.030	0.442	-2.615	0.147	0.318	0.342	3.133
ra_market_return_lag1	0.298	0.443	-2.615	0.128	0.318	0.342	3.133
ra_market_return_prev3_cum	0.764	0.507	-2.164	0.625	0.950	0.991	3.099

Continued on next page

Table 1 (continued)

Variable	Mean	Std. Dev.	Min	25%	50%	75%	Max
ra_market_return_prev6_cum	1.449	0.764	-1.631	1.114	1.697	1.946	4.093
Individual RA Returns							
Market RRG_lag1	-0.233	2.238	-6.024	-2.999	-2.666	-1.207	2.113
Market RRG_pos_lag1	0.010	0.047	0.000	0.000	0.000	0.000	2.113
Market RRG_neg_lag1	-0.243	2.076	-6.024	-2.999	-2.666	-1.207	0.000
Market RRG_prev3_cum	-0.544	2.915	-6.086	-6.904	-6.319	-4.878	2.080
Market RRG_pos_prev3_cum	0.010	0.042	0.000	0.000	0.000	0.000	2.080
Market RRG_neg_prev3_cum	-0.554	2.679	-6.086	-6.904	-6.319	-4.878	0.000
Market RRG_prev6_cum	-0.870	3.627	-7.859	-1.084	-9.974	-7.523	1.744
Market RRG_pos_prev6_cum	0.003	0.019	0.000	0.000	0.000	0.000	1.744
Market RRG_neg_prev6_cum	-0.872	3.556	-7.859	-1.084	-9.974	-7.523	0.000
Individual RRG							
Individual RRG_lag1	-0.003	0.071	-4.616	-0.016	0.000	0.010	4.700
Individual RRG_pos_lag1	0.011	0.060	0.000	0.000	0.000	0.010	4.700
Individual RRG_neg_lag1	-0.014	0.033	-4.616	-0.016	0.000	0.000	0.000
Individual RRG_prev3_cum	-0.008	0.095	-5.970	-0.035	0.000	0.017	7.848
Individual RRG_pos_prev3_cum	0.019	0.073	0.000	0.000	0.000	0.017	7.848
Individual RRG_neg_prev3_cum	-0.026	0.053	-5.970	-0.035	0.000	0.000	0.000
Individual RRG_prev6_cum	-0.013	0.129	-6.800	-0.051	-0.002	0.022	12.762
Individual RRG_pos_prev6_cum	0.024	0.098	0.000	0.000	0.000	0.022	12.762
Individual RRG_neg_prev6_cum	-0.037	0.072	-6.800	-0.051	-0.002	0.000	0.000

Notes. This table presents summary statistics for all variables used in the analysis. The sample includes 4.9 million observations. All financial variables are measured in RMB. Behavioral bias measures are normalized to [0,1] where available. RA refers to robo-advisor.

Table 2: Baseline: Demographics and Account Characteristics

Variable	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.787***	-0.139**
	(-6.745)	(-2.318)
Total Financial Assets$_{t-1}$	0.113***	-0.002
	(8.289)	(-1.192)
Risk Preference	0.109***	0.020***
	(6.289)	(3.875)
Age	0.049***	-0.020***
	(4.036)	(-3.127)
Gender	-0.102***	-0.026***
	(-9.097)	(-5.760)
Combined RA Dummy$_{t-1}$	0.719***	0.029***
	(32.763)	(2.713)
Baby Assets$_{t-1}$	-0.043***	-0.023***
	(-14.045)	(-7.205)
Length of Registration$_{t-1}$	0.062***	
	(24.867)	
Inverse Mills Ratio		0.242***
		(6.849)
Province Control	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.048	0.030
N	4,794,720	1,564,128

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across 48 months. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N equals mean monthly observations multiplied by $T = 48$.

Table 3: Baseline with Fund Experience and Skills

Variable	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.485***	-0.427
	(-2.966)	(-1.346)
Total Financial Assets$_{t-1}$	0.092***	-0.005**
	(8.542)	(-2.547)
Risk Preference	0.082***	0.017***
	(4.905)	(4.686)
Age	0.036***	-0.020***
	(3.105)	(-3.385)
Gender	-0.105***	-0.021***
	(-9.815)	(-5.619)
Combined RA Dummy$_{t-1}$	0.662***	0.004
	(30.714)	(0.361)
Baby Assets$_{t-1}$	-0.035***	-0.023***
	(-9.407)	(-6.876)
Experience of Fund Trading$_{t-1}$	0.385***	-0.326*
	(3.605)	(-1.872)
Selection Score$_{t-1}$	0.012**	0.002
	(2.203)	(1.082)
Timing Score (0–100)$_{t-1}$	0.002	0.009**
	(0.323)	(2.317)
Length of Registration$_{t-1}$	0.048***	
	(22.216)	
Inverse Mills Ratio		0.183***
		(4.896)
Province Control	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.046	0.045
N	4,479,936	1,560,048

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across 48 months. This specification augments the baseline model with fund trading experience (in months), selection skill, and timing score. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N equals mean monthly observations multiplied by $T = 48$.

Table 4: Baseline with Behavioral Biases

Variable	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.846***	-0.124*
	(-5.901)	(-1.935)
Total Financial Assets$_{t-1}$	0.056***	-0.001
	(7.376)	(-0.385)
Risk Preference	0.095***	0.020***
	(6.145)	(3.859)
Age	0.048***	-0.023***
	(3.773)	(-3.929)
Gender	-0.133***	-0.023***
	(-18.129)	(-4.515)
Combined RA Dummy$_{t-1}$	0.586***	0.027***
	(30.357)	(3.786)
Baby Assets$_{t-1}$	-0.031***	-0.024***
	(-5.781)	(-7.174)
Underdiversification$_{t-1}$	-0.256***	0.027***
	(-21.567)	(7.398)
Limited Attention Bias$_{t-1}$	-0.048***	-0.005***
	(-7.803)	(-3.193)
Disposition Effect Ratio$_{t-1}$	-0.061	0.002
	(-1.218)	(0.122)
Extrapolation Bias$_{t-1}$	0.003	-0.005***
	(0.925)	(-4.258)
Gambling Bias$_{t-1}$	-0.005*	-0.001
	(-1.830)	(-1.115)
Anchoring Bias$_{t-1}$	-0.008	0.001
	(-0.227)	(0.375)
Total Turnover$_{t-1}$	-1.238*	0.304
	(-1.792)	(1.384)
Speculative Turnover$_{t-1}$	-14.982***	-3.602***
	(-3.631)	(-3.022)
Length of Registration$_{t-1}$	0.065***	
	(20.198)	
Inverse Mills Ratio		0.241***
		(6.706)
Province Control	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.079	0.065
N	4,594,756	1,564,128

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across $T = 46$ months for this specification. This model extends the baseline specification by including behavioral bias measures: underdiversification score, attention bias, disposition effect ratio, extrapolation bias, gambling bias, anchoring bias, and turnover measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N equals mean monthly observations multiplied by T.

Table 5: Model Predictions and Empirical Evidence

	Underdiversification		Limited Attention		
Model	Adoption	Delegation	Adoption	Delegation	Consistent
Pure fixed cost	$-$	0	$-$	0	No
Uniform awareness	$-$	$+$	$-$	$+$	No
Selective awareness	$-$	$+$	$-$	$-$	Yes
Empirical estimates	-0.256	$+0.027$	-0.048	-0.005	
	(-21.6)	(7.4)	(-7.8)	(-3.2)	

Notes: Pure fixed cost model assumes biases affect discovery costs only with no awareness heterogeneity. Uniform awareness model assumes all biases trigger awareness updating upon adoption. Selective awareness model assumes awareness updating operates for correctable biases (underdiversification) but not cognitive constraints (limited attention). Fama-MacBeth t-statistics in parentheses.

Table 6: Demographics, Skills, and Behavioural Biases for Rule-Based Automation Sample

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=28)	
Variable	Probit (Auto$_{it}$)	Outcome (Auto$_{share}$)	Probit (Auto$_{it}$)	Outcome (Auto$_{share}$)	Probit (Auto$_{it}$)	Outcome (Auto$_{share}$)
Constant	-1.284***	-0.153	-1.514***	-0.129	-0.715***	-0.473
	(-35.626)	(-0.923)	(-18.881)	(-0.696)	(-10.746)	(-1.026)
Total Financial Assets$_{t-1}$	0.000***	0.000	0.000***	0.000	0.000***	0.000
	(10.907)	(0.879)	(9.023)	(0.792)	(9.423)	(1.068)
Risk Preference	0.069***	-0.004	0.034***	-0.005	0.051***	-0.005
	(5.248)	(-1.493)	(4.053)	(-1.536)	(3.971)	(-1.325)
Age	0.011***	0.000	0.010***	0.000	0.011***	0.001
	(26.475)	(0.840)	(18.555)	(0.781)	(16.720)	(0.855)
Gender	0.010	0.014	0.017	0.014	-0.011	0.028
	(0.736)	(0.828)	(1.019)	(0.818)	(-0.498)	(1.059)
Combined Auto Dummy$_{t-1}$	0.312***	0.017	0.231***	0.013	0.198***	0.048
	(41.834)	(0.757)	(15.269)	(0.640)	(13.261)	(0.988)
Baby Assets$_{t-1}$	-0.000***	-0.000**	-0.000***	-0.000*	-0.000***	-0.000
	(-10.856)	(-2.027)	(-13.108)	(-1.885)	(-7.771)	(-1.579)
Experience of Fund Trading$_{t-1}$			0.074**	-0.000		
			(2.173)	(-0.492)		
Selection Score$_{t-1}$			-0.240	0.150		
			(-0.947)	(1.087)		
Timing Score$_{t-1}$			-0.004***	-0.000		
			(-11.884)	(-1.073)		
Underdiversification$_{t-1}$					-0.715***	0.011
					(-9.487)	(0.468)
Limited Attention Bias$_{t-1}$					-0.219***	0.016
					(-3.242)	(1.364)
Disposition Effect Ratio$_{t-1}$					-0.000	-0.000
					(-1.486)	(-1.076)
Extrapolation Bias$_{t-1}$					0.141*	0.117
					(1.794)	(1.044)
Gambling Bias$_{t-1}$					-0.271***	-0.056
					(-3.450)	(-1.251)
Anchoring Bias$_{t-1}$					-0.080	0.059
					(-0.586)	(0.943)
Total Turnover$_{t-1}$					-0.162*	0.010
					(-1.916)	(0.433)
Speculative Turnover$_{t-1}$					0.152*	0.137
					(1.761)	(1.631)
Length of Registration	0.003***		0.002***		0.003***	
	(18.387)		(26.848)		(12.989)	
Inverse Mills Ratio		0.154		0.153		0.350
		(1.213)		(1.091)		(1.122)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2	0.029	0.014	0.036	0.022	0.068	0.070
N	4,794,720	679,392	4,479,936	678,384	2,797,984	419,916

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes baseline specification, Panel 2 adds fund experience and timing variables, and Panel 3 adds behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table 7: Robo-Advising versus Automated Trading

	Robo-Advising		Automated Trading	
Variable	Adoption	Delegation	Adoption	Allocation
Risk Preference	+	+	+	0
Gender (Female)	−	−	0	0
Timing Skill	0	+	−	0
Underdiversification	−	+	−	0
IMR (Selection)	+ (37% of mean)		0 (insignificant)	
Mean Allocation	10.17%		3.7%	
Adoption Rate	32.1%		32.9%	

Notes. Signs indicate statistically significant effects ($p < 0.05$). "0" denotes insignificance. IMR is the inverse Mills ratio coefficient from the Heckman second stage.

Table 8: Baseline with Fund Returns

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.713***	-0.112	-0.713***	-0.105	-0.707***	-0.116
	(-6.429)	(-1.520)	(-6.441)	(-1.481)	(-6.381)	(-1.590)
Total Financial Assets$_{t-1}$	0.089***	-0.003	0.089***	-0.003	0.089***	-0.003
	(10.307)	(-1.133)	(10.293)	(-1.231)	(10.416)	(-1.154)
Risk Preference	0.101***	0.020***	0.101***	0.019***	0.102***	0.020***
	(6.913)	(3.241)	(6.925)	(3.283)	(6.961)	(3.236)
Age	0.041***	-0.022***	0.041***	-0.022***	0.042***	-0.022***
	(3.330)	(-3.307)	(3.315)	(-3.329)	(3.332)	(-3.288)
Gender	-0.111***	-0.027***	-0.111***	-0.026***	-0.111***	-0.027***
	(-10.901)	(-4.769)	(-10.952)	(-4.792)	(-10.993)	(-4.773)
Combined RA Dummy$_{t-1}$	0.684***	0.018	0.684***	0.016	0.684***	0.018*
	(29.995)	(1.532)	(29.994)	(1.429)	(29.993)	(1.689)
Baby Assets$_{t-1}$	-0.034***	-0.022***	-0.034***	-0.022***	-0.034***	-0.022***
	(-7.384)	(-6.966)	(-7.423)	(-6.960)	(-7.442)	(-6.953)
Fund VW Return$_{t-1}$	0.001	0.002				
	(0.093)	(0.434)				
Fund VW Return Prev3 Cum			-0.000	0.006		
			(-0.033)	(1.087)		
Fund VW Return Prev6 Cum					0.001	0.006
					(0.140)	(0.938)
Length of Registration$_{t-1}$	0.057***		0.056***		0.057***	
	(20.421)		(20.206)		(20.337)	
Inverse Mills Ratio		0.224***		0.220***		0.225***
		(5.132)		(5.228)		(5.309)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2	0.042	0.031	0.042	0.031	0.042	0.031
N	4,385,376	1,534,128	4,385,376	1,534,128	4,385,376	1,534,128

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged fund portfolio returns, Panel 2 includes three-month cumulative fund returns, and Panel 3 includes six-month cumulative fund returns. All independent variables (except fund returns) are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N equals mean monthly observations multiplied by $T = 48$.

Table 9: Baseline with RA Returns

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.787***	-0.151**	-0.787***	-0.150**	-0.787***	-0.143**
	(-6.745)	(-2.547)	(-6.745)	(-2.529)	(-6.745)	(-2.379)
Total Financial Assets$_{t-1}$	0.113***	-0.003	0.113***	-0.003	0.113***	-0.003
	(8.289)	(-1.232)	(8.289)	(-1.252)	(8.289)	(-1.227)
Risk Preference	0.109***	0.020***	0.109***	0.020***	0.109***	0.020***
	(6.289)	(3.764)	(6.289)	(3.766)	(6.289)	(3.831)
Age	0.049***	-0.020***	0.049***	-0.020***	0.049***	-0.020***
	(4.036)	(-3.047)	(4.036)	(-3.050)	(4.036)	(-3.104)
Gender	-0.102***	-0.026***	-0.102***	-0.026***	-0.102***	-0.026***
	(-9.097)	(-5.815)	(-9.097)	(-5.827)	(-9.097)	(-5.802)
Combined RA Dummy$_{t-1}$	0.719***	0.032***	0.719***	0.032***	0.719***	0.030***
	(32.763)	(3.216)	(32.763)	(3.201)	(32.763)	(2.874)
Baby Assets$_{t-1}$	-0.043***	-0.024***	-0.043***	-0.024***	-0.043***	-0.024***
	(-14.045)	(-7.251)	(-14.045)	(-7.273)	(-14.045)	(-7.261)
RA VW Portfolio Return$_{t-1}$		-0.006*				
		(-1.959)				
RA VW Portfolio Return Prev3 Cum				-0.006**		
				(-1.996)		
RA VW Portfolio Return Prev6 Cum						-0.003
						(-0.916)
Length of Registration$_{t-1}$	0.062***		0.062***		0.062***	
	(24.867)		(24.867)		(24.867)	
Inverse Mills Ratio		0.249***		0.249***		0.245***
		(7.280)		(7.251)		(6.949)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.048	0.032	0.048	0.032	0.048	0.031
N	4,794,720	1,564,128	4,794,720	1,564,128	4,794,720	1,564,128

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged RA value-weighted portfolio return, Panel 2 includes three-month cumulative return, and Panel 3 includes six-month cumulative return. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table 10: Baseline with Fund and RA Returns

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.713***	-0.125	-0.713***	-0.117	-0.707***	-0.122
	(-6.429)	(-1.694)	(-6.441)	(-1.650)	(-6.381)	(-1.647)
Total Financial Assets$_{t-1}$	0.089***	-0.003	0.089***	-0.003	0.089***	-0.003
	(10.307)	(-1.170)	(10.293)	(-1.288)	(10.416)	(-1.180)
Risk Preference	0.101***	0.019***	0.101***	0.019***	0.102***	0.020***
	(6.913)	(3.119)	(6.925)	(3.156)	(6.961)	(3.174)
Age	0.041***	-0.022***	0.041***	-0.022***	0.042***	-0.022***
	(3.330)	(-3.216)	(3.315)	(-3.239)	(3.332)	(-3.251)
Gender	-0.111***	-0.027***	-0.111***	-0.026***	-0.111***	-0.027***
	(-10.901)	(-4.777)	(-10.952)	(-4.810)	(-10.993)	(-4.771)
Combined RA Dummy$_{t-1}$	0.684***	0.021*	0.684***	0.019*	0.684***	0.020*
	(29.995)	(1.905)	(29.994)	(1.808)	(29.993)	(1.833)
Baby Assets$_{t-1}$	-0.034***	-0.022***	-0.034***	-0.022***	-0.034***	-0.022***
	(-7.384)	(-6.996)	(-7.423)	(-7.007)	(-7.442)	(-6.992)
Fund VW Portfolio Return$_{t-1}$	0.001	0.002				
	(0.093)	(0.563)				
RA VW Portfolio Return$_{t-1}$		-0.007**				
		(-2.426)				
Fund VW Portfolio Return Prev3 Cum			-0.000	0.007		
			(-0.033)	(1.160)		
RA VW Portfolio Return Prev3 Cum				-0.007**		
				(-2.340)		
Fund VW Portfolio Return Prev6 Cum					0.001	0.006
					(0.140)	(0.951)
RA VW Portfolio Return Prev6 Cum						-0.004
						(-1.101)
Length of Registration$_{t-1}$	0.057***		0.056***		0.057***	
	(20.421)		(20.206)		(20.337)	
Inverse Mills Ratio		0.233***		0.228***		0.229***
		(5.384)		(5.481)		(5.359)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.042	0.033	0.042	0.034	0.042	0.032
Median Pseudo R^2 / R^2	0.039	0.027	0.039	0.027	0.039	0.024
N	4,385,376	1,534,128	4,385,376	1,534,128	4,385,376	1,534,128

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged portfolio returns, Panel 2 includes three-month cumulative returns, and Panel 3 includes six-month cumulative returns. Fund VW Portfolio Return is the value-weighted portfolio return in the fund account (appears in both Probit and Outcome). RA VW Portfolio Return is the value-weighted portfolio return in the retirement account (appears only in Outcome). All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table 11: Baseline with Market RRG

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.689***	-0.133***	-0.707***	-0.151***	-0.712***	-0.170*
	(-5.398)	(-1.760)	(-6.608)	(-1.850)	(-7.534)	(-1.805)
Total Financial Assets$_{t-1}$	0.089***	-0.003	0.089***	-0.003	0.089***	-0.003
	(10.318)	(-1.144)	(10.304)	(-1.252)	(10.446)	(-1.207)
Risk Preference	0.101***	0.020***	0.101***	0.019***	0.102***	0.019***
	(6.914)	(3.227)	(6.932)	(3.274)	(6.971)	(3.194)
Age	0.041***	-0.022***	0.041***	-0.022***	0.042***	-0.022***
	(3.337)	(-3.299)	(3.319)	(-3.344)	(3.338)	(-3.302)
Gender	-0.111***	-0.026***	-0.111***	-0.026***	-0.111***	-0.026***
	(-10.911)	(-4.771)	(-10.977)	(-4.792)	(-11.038)	(-4.747)
Combined RA Dummy$_{t-1}$	0.684***	0.018	0.684***	0.015	0.683***	0.017
	(29.961)	(1.529)	(29.960)	(1.369)	(29.987)	(1.577)
Baby Assets$_{t-1}$	-0.034***	-0.022***	-0.034***	-0.022***	-0.035***	-0.022***
	(-7.381)	(-6.977)	(-7.418)	(-6.969)	(-7.413)	(-6.959)
Market RRG$_{t-1}$	0.040	-0.006				
	(0.974)	(-0.298)				
Market RRG Prev3 Cum			0.032	0.016		
			(0.976)	(0.680)		
Market RRG Prev6 Cum					0.041	0.017
					(1.184)	(0.638)
Length of Registration$_{t-1}$	0.057***		0.057***		0.057***	
	(20.588)		(20.288)		(20.530)	
Inverse Mills Ratio		0.224***		0.218***		0.221***
		(5.169)		(5.219)		(5.279)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.042	0.031	0.042	0.032	0.042	0.031
N	4,385,376	1,534,128	4,385,280	1,534,080	4,385,232	1,534,080

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates are from Heckman two-stage selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged market RRG, Panel 2 includes three-month cumulative market RRG, and Panel 3 includes six-month cumulative market RRG. All covariates are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N equals mean monthly observations multiplied by $T = 48$.

Table 12: Baseline with Individual RRG

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.787***	-0.105**	-0.787***	-0.101**	-0.787***	-0.109**
	(-6.745)	(-1.997)	(-6.745)	(-1.963)	(-6.745)	(-2.032)
Total Financial Assets$_{t-1}$	0.113***	-0.003***	0.113***	-0.003***	0.113***	-0.003***
	(8.289)	(-1.304)	(8.289)	(-1.369)	(8.289)	(-1.265)
Risk Preference	0.109***	0.018***	0.109***	0.018***	0.109***	0.018***
	(6.289)	(3.739)	(6.289)	(3.742)	(6.289)	(3.751)
Age	0.049***	-0.019***	0.049***	-0.019***	0.049***	-0.019***
	(4.036)	(-3.239)	(4.036)	(-3.242)	(4.036)	(-3.212)
Gender	-0.102***	-0.023***	-0.102***	-0.022***	-0.102***	-0.023***
	(-9.097)	(-5.637)	(-9.097)	(-5.668)	(-9.097)	(-5.604)
Combined RA Dummy$_{t-1}$	0.719***	0.021**	0.719***	0.020**	0.719***	0.022**
	(32.763)	(2.253)	(32.763)	(2.114)	(32.763)	(2.265)
Baby Assets$_{t-1}$	-0.043***	-0.022***	-0.043***	-0.022***	-0.043***	-0.023***
	(-14.045)	(-7.016)	(-14.045)	(-7.021)	(-14.045)	(-6.987)
Individual RRG$_{t-1}$		-0.007				
		(-1.500)				
Individual RRG Prev3 Cum				0.006		
				(1.021)		
Individual RRG Prev6 Cum						0.010
						(1.488)
Length of Registration$_{t-1}$	0.062***		0.062***		0.062***	
	(24.867)		(24.867)		(24.867)	
Inverse Mills Ratio		0.214***		0.212***		0.215***
		(6.781)		(6.755)		(6.736)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.048	0.032	0.048	0.032	0.048	0.030
N	4,794,720	1,534,128	4,794,720	1,533,744	4,794,720	1,533,504

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged individual RRG (Relative Return Gap), Panel 2 includes three-month cumulative RRG, and Panel 3 includes six-month cumulative RRG. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table 13: Baseline with Asymmetric Market RRG

	Panel 1 (T=47)		Panel 2 (T=47)		Panel 3 (T=46)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant$_{t-1}$	-0.894***	-0.132	-1.008***	-0.140	-1.164***	-0.157
	(-6.736)	(-1.792)	(-4.797)	(-1.745)	(-4.814)	(-1.745)
Total Financial Assets$_{t-1}$	0.089***	-0.003	0.089***	-0.003	0.089***	-0.003
	(10.297)	(-1.138)	(10.204)	(-1.220)	(10.259)	(-1.453)
Risk Preference	0.101***	0.020***	0.101***	0.019***	0.099***	0.018***
	(6.710)	(3.160)	(6.776)	(3.211)	(6.794)	(3.313)
Age	0.041***	-0.022***	0.041***	-0.022***	0.044***	-0.021***
	(3.255)	(-3.244)	(3.256)	(-3.264)	(3.648)	(-3.313)
Gender	-0.111***	-0.027***	-0.111***	-0.026***	-0.110***	-0.025***
	(-10.813)	(-4.692)	(-10.772)	(-4.705)	(-11.022)	(-4.986)
Combined RA Dummy$_{t-1}$	0.683***	0.016	0.684***	0.015	0.687***	0.015
	(29.512)	(1.424)	(29.366)	(1.312)	(33.041)	(1.526)
Baby Assets$_{t-1}$	-0.034***	-0.022***	-0.034***	-0.022***	-0.034***	-0.022***
	(-7.141)	(-6.832)	(-7.255)	(-6.842)	(-7.063)	(-6.815)
Market RRG Pos$_{t-1}$	-0.919**	0.004				
	(-2.497)	(0.153)				
Market RRG Neg$_{t-1}$	0.085	-0.005				
	(1.734)	(-0.246)				
Market RRG Pos Prev3 Cum			-1.134	0.001		
			(-1.726)	(0.036)		
Market RRG Neg Prev3 Cum			0.066	0.009		
			(1.679)	(0.408)		
Market RRG Pos Prev6 Cum					-2.899*	-0.005
					(-1.864)	(-0.486)
Market RRG Neg Prev6 Cum					0.078	0.019
					(1.546)	(0.754)
Length of Registration$_{t-1}$	0.056***		0.057***		0.058***	
	(20.481)		(19.860)		(22.100)	
Inverse Mills Ratio		0.223***		0.218***		0.214***
		(5.027)		(5.104)		(5.584)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.042	0.032	0.042	0.032	0.042	0.030
Median Pseudo R^2 / R^2	0.039	0.024	0.039	0.025	0.039	0.023
N	4,287,975	1,503,919	4,287,424	1,503,454	4,200,328	1,486,696

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged positive and negative market RRG separately, Panel 2 includes three-month cumulative positive and negative market RRG, and Panel 3 includes six-month cumulative positive and negative market RRG. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table 14: Baseline with Asymmetric Individual RRG

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	-0.787***	-0.100*	-0.787***	-0.101*	-0.787***	-0.092**
	(-6.745)	(-1.946)	(-6.745)	(-1.913)	(-6.745)	(-2.045)
Total Financial Assets$_{t-1}$	0.113***	-0.003	0.113***	-0.003	0.113***	-0.003*
	(8.289)	(-1.378)	(8.289)	(-1.349)	(8.289)	(-1.726)
Risk Preference	0.109***	0.017***	0.109***	0.017***	0.109***	0.017***
	(6.289)	(3.756)	(6.289)	(3.707)	(6.289)	(4.120)
Age	0.049***	-0.019***	0.049***	-0.019***	0.049***	-0.020***
	(4.036)	(-3.255)	(4.036)	(-3.247)	(4.036)	(-3.295)
Gender	-0.102***	-0.022***	-0.102***	-0.022***	-0.102***	-0.022***
	(-9.097)	(-5.757)	(-9.097)	(-5.587)	(-9.097)	(-6.031)
Combined RA Dummy$_{t-1}$	0.719***	0.020**	0.719***	0.020**	0.719***	0.019**
	(32.763)	(2.143)	(32.763)	(2.065)	(32.763)	(2.072)
Baby Assets$_{t-1}$	-0.043***	-0.022***	-0.043***	-0.022***	-0.043***	-0.023***
	(-14.045)	(-7.037)	(-14.045)	(-7.008)	(-14.045)	(-7.297)
Individual RRG Positive$_{t-1}$		-0.013*				
		(-1.860)				
Individual RRG Negative$_{t-1}$		-0.005				
		(-1.385)				
Individual RRG Positive Prev3 Cum				-0.002		
				(-0.332)		
Individual RRG Negative Prev3 Cum				-0.002		
				(-0.383)		
Individual RRG Positive Prev6 Cum						0.005
						(1.110)
Individual RRG Negative Prev6 Cum						-0.006
						(-1.059)
Length of Registration$_{t-1}$	0.062***		0.062***		0.062***	
	(24.867)		(24.867)		(24.867)	
Inverse Mills Ratio		0.212***		0.211***		0.208***
		(6.813)		(6.714)		(7.241)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.048	0.032	0.048	0.033	0.048	0.033
N	4,794,720	1,534,128	4,794,720	1,533,744	4,794,720	1,477,440

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged positive and negative individual RRG (Relative Return Gap), Panel 2 includes three-month cumulative positive and negative RRG, and Panel 3 includes six-month cumulative positive and negative RRG. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table 15: Demographics, Skills, and Behavioural Biases for First Use Sample

	Panel 1 (T=44)		Panel 2 (T=44)		Panel 3 (T=37)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	-2.114***	0.108	-2.134***	-0.711	-2.127***	0.637
	(-58.106)	(0.251)	(-26.110)	(-0.974)	(-38.242)	(0.638)
Total Financial Assets$_{t-1}$	-0.005	-0.050***	-0.018	-0.065***	-0.046*	0.019
	(-0.228)	(-3.660)	(-0.868)	(-2.681)	(-1.801)	(0.317)
Risk Preference	0.056***	0.004	0.056***	0.016	0.047***	0.011**
	(4.301)	(0.866)	(5.207)	(1.484)	(3.632)	(2.031)
Age	0.015**	-0.020***	0.013*	-0.002	0.015*	-0.019**
	(2.127)	(-3.819)	(1.771)	(-0.146)	(1.874)	(-2.053)
Gender	-0.112***	-0.005	-0.114***	-0.015	-0.135***	0.039
	(-9.453)	(-0.260)	(-10.103)	(-0.570)	(-10.937)	(0.788)
Combined RA Dummy$_{t-1}$	0.311***	-0.085*	0.283***	-0.017	0.220***	-0.110
	(15.088)	(-1.686)	(15.552)	(-0.227)	(11.430)	(-1.133)
Baby Assets$_{t-1}$	0.024***	0.003	0.025***	0.008	0.037***	-0.021
	(6.728)	(0.463)	(5.673)	(0.822)	(8.156)	(-0.814)
Experience of Fund Trading$_{t-1}$			-0.055	-0.280**		
			(-1.234)	(-2.088)		
Selection Score$_{t-1}$			0.007	-0.014		
			(1.507)	(-0.732)		
Timing Score$_{t-1}$			-0.085***	-0.010		
			(-4.580)	(-0.373)		
Underdiversification$_{t-1}$					-0.134***	0.075*
					(-7.590)	(1.648)
Limited Attention Bias$_{t-1}$					0.002	0.001
					(0.150)	(0.349)
Disposition Effect Ratio$_{t-1}$					-0.163*	3.414
					(-1.891)	(1.021)
Extrapolation Bias$_{t-1}$					-0.017**	0.007
					(-2.313)	(0.549)
Gambling Bias$_{t-1}$					-0.003	-0.001
					(-0.786)	(-0.308)
Anchoring Bias$_{t-1}$					-0.006	-0.026
					(-0.147)	(-1.200)
Total Turnover$_{t-1}$					-0.204***	10.018***
					(-3.697)	(3.022)
Speculative Turnover$_{t-1}$					-0.060***	-7.087
					(-2.928)	(-1.453)
Length of Registration	0.027***		0.026***		0.029***	
	(3.608)		(3.615)		(3.812)	
Inverse Mills Ratio		0.042		0.250		-0.109
		(0.246)		(0.892)		(-0.274)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2	0.021	0.073	0.028	0.081	0.038	0.124
N	2,389,728	62,656	2,099,240	58,564	2,006,251	54,131

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. This analysis focuses on first-time RA users only. Panel 1 includes baseline specification, Panel 2 adds fund experience and timing variables, and Panel 3 adds behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months). The smaller N and T values compared to the full sample reflect filtering out months where users do not meet first-use criteria.

Table 16: Demographics, Skills, and Behavioural Biases for Continuation Use (Used at t-1)

	Panel 1 (T=47)		Panel 2 (T=44)		Panel 3 (T=37)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	1.902***	0.056**	-2.134***	-0.711	-2.127***	0.637
	(67.503)	(2.164)	(-26.110)	(-0.974)	(-38.242)	(0.638)
Total Financial Assets$_{t-1}$	0.049***	-0.008***	-0.018	-0.065***	-0.046*	0.019
	(4.081)	(-5.767)	(-0.868)	(-2.681)	(-1.801)	(0.317)
Risk Preference	-0.003	-0.004	0.056***	0.016	0.047***	0.011**
	(-0.828)	(-1.048)	(5.207)	(1.484)	(3.632)	(2.031)
Age	0.068***	-0.004	0.013*	-0.002	0.015*	-0.019**
	(9.062)	(-1.318)	(1.771)	(-0.146)	(1.874)	(-2.053)
Gender	0.077***	0.017***	-0.114***	-0.015	-0.135***	0.039
	(7.965)	(2.864)	(-10.103)	(-0.570)	(-10.937)	(0.788)
Combined RA Dummy$_{t-1}$	0.201***	-0.034***	0.283***	-0.017	0.220***	-0.110
	(12.808)	(-4.479)	(15.552)	(-0.227)	(11.430)	(-1.133)
Baby Assets$_{t-1}$	0.001	-0.020***	0.025***	0.008	0.037***	-0.021
	(0.173)	(-5.817)	(5.673)	(0.822)	(8.156)	(-0.814)
Experience of Fund Trading$_{t-1}$			-0.055	-0.280**		
			(-1.234)	(-2.088)		
Selection Score$_{t-1}$			0.007	-0.014		
			(1.507)	(-0.732)		
Timing Score 0_100$_{t-1}$			-0.085***	-0.010		
			(-4.580)	(-0.373)		
Underdiversification$_{t-1}$					-0.134***	0.075*
					(-7.590)	(1.648)
Limited Attention Bias$_{t-1}$					0.002	0.001
					(0.150)	(0.349)
Disposition Effect Ratio$_{t-1}$					-0.163*	3.414
					(-1.891)	(1.021)
Extrapolation Bias$_{t-1}$					-0.017**	0.007
					(-2.313)	(0.549)
Gambling Bias$_{t-1}$					-0.003	-0.001
					(-0.786)	(-0.308)
Anchoring Bias$_{t-1}$					-0.006	-0.026
					(-0.147)	(-1.200)
Total Turnover$_{t-1}$					-0.204***	10.018***
					(-3.697)	(3.022)
Speculative Turnover$_{t-1}$					-0.060***	-7.087
					(-2.928)	(-1.453)
Length of Registration$_{t-1}$	0.038***		0.026***		0.029***	
	(11.952)		(3.615)		(3.812)	
Inverse Mills Ratio		2.177***		0.250		-0.109
		(7.039)		(0.892)		(-0.274)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.016	0.031	0.028	0.081	0.038	0.124
N	1,463,217	1,422,549	2,099,240	58,564	2,005,251	54,131

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes basic controls, Panel 2 adds experience and timing measures, and Panel 3 includes comprehensive behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table 17: Demographics, Skills, and Behavioural Biases for Re-entry After Breaks

	Panel 1 (T=46)		Panel 2 (T=44)		Panel 3 (T=37)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Constant	-2.727***	-0.618	-2.134***	-0.711	-2.127***	0.637
	(-29.917)	(-0.456)	(-26.110)	(-0.974)	(-38.242)	(0.638)
Total Financial Assets$_{t-1}$	-0.029***	-0.095***	-0.018***	-0.065***	-0.046***	0.019
	(-1.551)	(-3.870)	(-0.868)	(-2.681)	(-1.801)	(0.317)
Risk Preference	0.069***	0.056	0.056***	0.016	0.047***	0.011
	(3.832)	(1.608)	(5.207)	(1.484)	(3.632)	(2.031)
Age	-0.063***	-0.047	0.013*	-0.002	0.015*	-0.019**
	(-3.027)	(-1.110)	(1.771)	(-0.146)	(1.874)	(-2.053)
Gender	-0.160***	0.040	-0.114***	-0.015	-0.135***	0.039
	(-7.873)	(0.507)	(-10.103)	(-0.570)	(-10.937)	(0.788)
Combined RA Dummy$_{t-1}$	0.069***	-0.080	0.283***	-0.017	0.220***	-0.110
	(3.706)	(-1.117)	(15.552)	(-0.227)	(11.430)	(-1.133)
Baby Assets$_{t-1}$	0.011**	0.015*	0.025***	0.008	0.037***	-0.021
	(2.103)	(1.725)	(5.673)	(0.822)	(8.156)	(-0.814)
Experience of Fund Trading$_{t-1}$			-0.055	-0.280**		
			(-1.234)	(-2.088)		
Selection Score$_{t-1}$			0.007	-0.014		
			(1.507)	(-0.732)		
Timing Score$_{t-1}$			-0.085***	-0.010		
			(-4.580)	(-0.373)		
Underdiversification$_{t-1}$					-0.134***	0.075
					(-7.590)	(1.648)
Limited Attention Bias$_{t-1}$					0.002	0.001
					(0.150)	(0.349)
Disposition Effect Ratio$_{t-1}$					-0.163*	3.414
					(-1.891)	(1.021)
Extrapolation Bias$_{t-1}$					-0.017**	0.007
					(-2.313)	(0.549)
Gambling Bias$_{t-1}$					-0.003	-0.001
					(-0.786)	(-0.308)
Anchoring Bias$_{t-1}$					-0.006	-0.026
					(-0.147)	(-1.200)
Total Turnover$_{t-1}$					-0.204***	10.018***
					(-3.697)	(3.022)
Speculative Turnover$_{t-1}$					-0.060***	-7.087
					(-2.928)	(-1.453)
Length of Registration$_{t-1}$	-0.001		0.026***		0.029***	
	(-0.088)		(3.615)		(3.812)	
Inverse Mills Ratio		0.214***		0.250***		-0.109
		(0.464)		(0.892)		(-0.274)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.023	0.094	0.028	0.081	0.038	0.124
Median Pseudo R^2 / R^2	0.017	0.083	0.023	0.078	0.036	0.115
N	1,702,472	9,752	2,099,240	58,564	2,005,251	54,131

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes basic controls, Panel 2 adds experience and timing measures, and Panel 3 includes comprehensive behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table 18: Dynamic Participation and Coefficient Patterns Across Margins

	General		First-Use		Continuation		Re-entry	
Variable	Adopt	Deleg	Adopt	Deleg	Adopt	Deleg	Adopt	Deleg
Wealth	+	0	0	−	+	−	0	−
Age	+	−	+	−	+	0	−	0
Gender (Female)	−	−	−	0	+	+	−	0
Prior RA	+	+	+	−	+	−	+	0
Liquidity	−	−	+	0	0	−	+	+
Tenure	+	x	+	x	+	x	0	x
IMR		+		0		++		0

Notes. Signs indicate the direction of statistically significant effects. "0" denotes insignificance. "++" denotes a very large effect. "x" indicates exclusion from the outcome equation.

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A1. Online Appendix

A1.1. External Validity and Platform Comparisons

BangNiTou charges annual management fees of approximately 0.20 to 0.50 percent of assets under management. Table A1 compares these fees with those of major global robo-advisors.

Table A1: Robo-Advisor Fee Comparison

Platform	Annual Fee	Minimum	Region
BangNiTou	0.20–0.50%	100 to 800 RMB ($15–$115)	China
Betterment	0.25%	$0	United States
Wealthfront	0.25%	$500	United States
Vanguard Digital	0.20–0.25%	$100	United States
Vanguard Personal	0.35–0.40%	$50,000	United States

BangNiTou's fee structure is transparent and proportional to assets, consistent with industry standards documented by Fisch et al. (2019) and Reher and Sokolinski (2024). Vanguard's fee structure is somewhat more complex owing to the multiple product tiers it offers.[18]

BangNiTou employs modern portfolio theory with human advisor oversight to construct diversified mutual fund portfolios. After collecting investor information through an online suitability questionnaire, the platform recommends allocations across equity and fixed-income mutual funds tailored to the investor's risk profile. This approach follows the methodology described in Beketov et al. (2018) and Torno and Schildmann (2020).

Portfolios are rebalanced automatically when allocations drift beyond pre-specified thresholds. This design follows the standard robo-advisory model of delegated, algorithm-driven portfolio management with periodic rebalancing, consistent with Betterment, Wealthfront, and other MPT-based robo-advisors globally (D'Acunto et al., 2019; Rossi & Utkus, 2024).

The demographic profile of BangNiTou users is broadly comparable to that of U.S. robo-advisor users documented by Baulkaran and Jain (2023).

Mean age in our sample is 32.5 years, consistent with the 25 to 45 age range reported for Betterment and Wealthfront users. The user base is predominantly urban, educated, and digitally engaged, consistent with early-adopter profiles in fintech (Gomber et al., 2018; Philippon, 2019).

While absolute income and wealth levels differ substantially between China and the United States, the relative position of robo-advisor users within their respective national income distributions appears similar. Both populations are middle-to-upper-middle class, financially engaged, and comfortable with digital financial services. This pattern aligns with evidence from Hong et al. (2025) on fintech platform adoption in China.

BangNiTou operates under Chinese securities regulations requiring robo-advisors to be licensed as investment advisory firms, maintain capital adequacy, and comply with suitability and disclosure requirements. These regulations are broadly comparable to U.S. SEC and FINRA requirements for

[18]To be eligible for Vanguard Digital Advisor, an investor must hold $5 or more in an employer-sponsored retirement plan at Vanguard, or $100 or more in IRAs and taxable accounts owned individually or as joint tenants with rights of survivorship. Eligibility for Personal Advisor requires $250,000 or more in an employer-sponsored retirement plan, $50,000 or more in IRAs and taxable accounts, or $250,000 in total across all account types at Vanguard.

registered investment advisors (Baker & Dellaert, 2018). BangNiTou is subject to fiduciary standards requiring that recommendations serve the client's best interest, similar to the standards analyzed by Foerster et al. (2017) in the U.S. context.

The primary feature distinguishing BangNiTou from standalone global robo-advisors is its integration within the Alipay super-app. Unlike Betterment, Wealthfront, or Vanguard's robo services, which require separate account opening and funding via bank transfer, BangNiTou is accessible within the same interface where users conduct daily payments and trade self-directed funds.

This integration has three implications for investor behavior.

First, adoption frictions are minimized. Investors do not need to establish separate brokerage relationships or link external bank accounts. Portfolios are funded directly from Alipay wallet balances, which lowers the fixed cost of initial adoption and potentially increases experimentation rates. The friction reduction resonates with evidence from Thaler and Sunstein (2008) on how choice architecture affects financial decisions.

Second, switching costs are negligible. Investors reallocate between self-directed and robo-advised portfolios seamlessly within the same application. This facilitates the dynamic participation patterns we observe in the data. Standalone robo-advisors may exhibit stickier participation because exiting and re-entering involves greater operational cost.

Third, comparative information is salient. Self-directed and robo-advised returns are displayed in the same application, allowing investors to observe relative performance directly without aggregating data across platforms. This aids identification of performance-based learning but may amplify performance comparisons relative to settings with separate accounts. The salience of comparative returns connects to evidence on attention-driven trading (Barber & Odean, 2008; Barber et al., 2022).

The integrated design has ambiguous implications for external validity.

Lower barriers may inflate magnitudes. The low fixed costs and switching costs in our setting may produce higher adoption and cycling rates than standalone platforms. Effect sizes for adoption determinants may therefore be larger than in settings with greater frictions.

Qualitative patterns should nonetheless generalize. The opposite signs we document reflect fundamental tensions between exposure and commitment that should operate in any setting where participation is partial and reversible. The adverse selection patterns reflect behavioural preferences for control that are not platform-specific. Bianchi and Briere (2026) document similar patterns of human-robot interaction in investment decisions across different institutional settings.

Integration strengthens identification. Observing both delegated and self-directed portfolios within the same account eliminates confounds from unobserved holdings elsewhere or differential attrition across platforms. Low switching costs enable clean identification of dynamic participation. Salient performance comparisons enable precise tests of learning.

Our contribution is to establish that participation and delegation are governed by distinct mechanisms, that these mechanisms produce systematic opposite signs, and that demand evolves dynamically across participation phases. Whether effect magnitudes differ between integrated and standalone settings is an important question for subsequent work. The qualitative patterns should generalize to any environment where delegation is partial and reversible.

Total assets grow from approximately 5 billion yuan to over 10 billion yuan over the sample period.

Mutual funds represent the dominant share, ranging from 50 to 70 percent throughout. Robo-advised assets remain relatively stable at approximately 5 percent of total financial assets. This composition, with substantial self-directed positions coexisting alongside robo-advised portfolios, facilitates direct comparison of delegation choices and confirms that investors actively manage both margins. The co-existence of active and passive management within individual portfolios echoes the household finance patterns documented by Calvet et al. (2007).

A1.2. Methodology Details

The platform-wide population exhibits extreme class imbalance. Monthly robo-advisor adoption incidence is approximately 1 adopter per 100 non-adopters. Our stratified sample oversamples adopters (70,000) relative to non-adopters (30,000) to ensure sufficient variation for studying both margins of the participation decision.

We implement month-specific calibration weights to restore population representativeness, following the choice-based sampling framework of Manski and Lerman (1977). For each month t, let p_t^{samp} denote the sample adoption rate and $p^{\text{pop}} = 0.01$ the population rate. Observations receive weights

$$w_{it} = \frac{p^{\text{pop}}}{p_t^{\text{samp}}} \quad \text{if } d_{it} = 1, \tag{22}$$

$$w_{it} = \frac{1 - p^{\text{pop}}}{1 - p_t^{\text{samp}}} \quad \text{if } d_{it} = 0. \tag{23}$$

Weights are normalized to unit mean within each month. These weights are applied in both stages of the Heckman procedure. The first-stage probit is estimated using weighted maximum likelihood, and the second-stage outcome equation is estimated by weighted least squares.

The inverse Mills ratio is computed from the first-stage probit as

$$\text{IMR}_{it} = \frac{\phi(\mathbf{Z}'_{it-1}\hat{\boldsymbol{\gamma}})}{\Phi(\mathbf{Z}'_{it-1}\hat{\boldsymbol{\gamma}})}, \tag{24}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal density and cumulative distribution function (Heckman, 1979).

The IMR coefficient δ measures selection on unobservables. Under the assumption that the error terms in the selection and outcome equations are jointly normal with correlation ρ, we have $\delta = \rho\sigma_\varepsilon$, where σ_ε is the standard deviation of the outcome equation error. A positive δ indicates that unobserved factors increasing adoption propensity, such as trust in automation or openness to experimentation, also increase delegation intensity among adopters. This interpretation connects to the trust-based framework developed by Gennaioli et al. (2015) and Guiso et al. (2008).

Standard errors are computed from the time-series distribution of monthly coefficient estimates following Fama and MacBeth (1973)

$$\text{SE}(\bar{\beta}_k) = \frac{1}{\sqrt{T}} \left[\frac{1}{T-1} \sum_{t=1}^{T} (\hat{\beta}_{kt} - \bar{\beta}_k)^2 \right]^{1/2}. \tag{25}$$

To account for potential autocorrelation in the time series of monthly estimates, we also compute Newey-West standard errors with automatic lag selection (Newey & West, 1987). Results are robust to the choice of standard error estimator.

For months with insufficient variation, specifically those with fewer uncensored observations than parameters or with near-constant regressors, we exclude that month from the Fama-MacBeth averages. This occurs in fewer than 5 of 49 months. Results are robust to including or excluding these edge cases.

A1.3. Variable Construction Details

This section describes the construction of key variables used in the analysis. Table A2 summarizes the behavioural bias measures.

Table A2: Summary of Behavioural Bias Measures

Bias	Key References	Measurement Approach
Limited Attention	Barber and Odean (2008)	Share of trades in attention-grabbing funds
Underdiversification	Goetzmann and Kumar (2008)	HHI, return correlation, normalized variance
Extrapolation	Greenwood and Shleifer (2014)	Share of trades in momentum funds
Gambling/Lottery	Kumar (2009)	Share of trades in lottery-type funds
Disposition Effect	Odean (1998)	PGR minus PLR
Overconfidence	Barber and Odean (2000)	Total and speculative turnover
Anchoring	New measure	Share of trades near 52-week highs/lows

Notes. PGR is the proportion of gains realized. PLR is the proportion of losses realized. HHI is the Herfindahl-Hirschman Index of portfolio concentration. All measures are converted to within-month percentile ranks prior to estimation.

Fund trading experience measures cumulative months with active mutual fund holdings

$$\text{Experience}_{it} = \sum_{\tau=1}^{t-1} \mathbf{1}[\text{Fund Holdings}_{i\tau} > 0]. \tag{26}$$

This measure captures learning-by-doing in financial markets, consistent with evidence from Nicolosi et al. (2009) and Gervais and Odean (2001).

For each fund f held by investor i in month t, we compute excess return relative to the Morningstar category average

$$\text{Excess Return}_{ift} = r_{ft} - \bar{r}_{c(f),t}, \tag{27}$$

where r_{ft} is fund f's return and $\bar{r}_{c(f),t}$ is the equal-weighted average return of funds in category $c(f)$.

Investor-level selection is the value-weighted average

$$\text{Selection}_{it} = \sum_{f \in \mathcal{F}_{it}} w_{ift} \cdot \text{Excess Return}_{ift}, \tag{28}$$

where $w_{ift} = \text{Holdings}_{if,t-1} / \sum_{f'} \text{Holdings}_{if',t-1}$ are beginning-of-month portfolio weights.

We convert selection to a within-month percentile rank ranging from 0 to 100 and forward-fill for months with no active trading. This approach to measuring investor skill follows the methodology in Calvet et al. (2007) and Grinblatt and Keloharju (2009).

Timing isolates returns attributable to within-month trading

$$\text{Timing Return}_{ift} = \frac{\text{Cumulative PnL}_{ift}}{\text{Holdings}_{if,t-1}} - \text{Holding Return}_{ift}, \tag{29}$$

where Cumulative PnL includes mark-to-market gains plus realized gains and losses from trades, and Holding Return is the passive buy-and-hold return.

Investor-level timing is value-weighted

$$\text{Timing}_{it} = \sum_{f \in \mathcal{F}_{it}} w_{if,t-1} \cdot \text{Timing Return}_{ift}. \tag{30}$$

We convert to percentile rank and forward-fill. By construction, selection and timing are orthogonal. Selection conditions on holding for the full month, whereas timing measures returns from position adjustments within the month.

Underdiversification is a well-documented behavioural bias whereby investors hold concentrated portfolios that fail to exploit diversification benefits (Goetzmann & Kumar, 2008; Huberman, 2001; Polkovnichenko, 2005). We construct a composite score from three components following Hao et al. (2022).

The first component is portfolio concentration, measured by the Herfindahl-Hirschman Index of fund weights

$$\text{HHI}_{it} = \sum_{f} w_{ift}^2. \tag{31}$$

A portfolio equally weighted across N funds has HHI $= 1/N$, while a portfolio concentrated in a single fund has HHI $= 1$.

The second component is return comovement, computed as the portfolio-weighted average pairwise correlation of fund returns. High correlation indicates that the investor's holdings move together, providing limited diversification benefit.

The third component follows Goetzmann and Kumar (2008) in computing normalized portfolio variance

$$\text{NPV}_{it} = \frac{\text{Var}(R_{p,it})}{\bar{\text{Var}}(R_{f,it})}, \tag{32}$$

where $\text{Var}(R_{p,it})$ is the variance of the investor's portfolio return and $\bar{\text{Var}}(R_{f,it})$ is the average variance of individual fund returns in the portfolio. A well-diversified portfolio has NPV substantially below one. Our underdiversification measure is the negative of diversification, so higher values indicate greater concentration.

Each component is converted to a within-month percentile rank ranging from 0 to 1. The underdiversification score is the simple average of available components.

Limited attention bias reflects investors' tendency to trade assets that capture their attention rather than systematically evaluating all available options (Barber & Odean, 2008; Barber et al., 2022). Following Seasholes and Wu (2007) and Hao et al. (2022), we identify attention-grabbing funds based on characteristics that make them salient to retail investors, tailored to the institutional setting of mutual fund trading on Alipay.

A fund is classified as attention-grabbing in month t if it satisfies any of the following criteria. The

fund ranks in the top 10 percent of price gainers over the prior month. The fund ranks in the top 10 percent by Sharpe ratio. The fund ranks in the top 10 percent of losers, since extreme negative returns also attract attention. The fund ranks in the top 10 percent of within-industry gainers. The fund was newly issued within the past three months. The fund ranks in the top 10 percent by 12-month cumulative returns. The fund ranks in the most stable 10 percent by return volatility.

Attention bias is the share of trading value directed to attention-grabbing funds

$$\text{Attention}_{it} = \frac{\sum_{f \in \text{Attention}} |\text{Trades}_{ift}|}{\sum_{f} |\text{Trades}_{ift}|}. \tag{33}$$

A higher percentage indicates a greater probability that the investor is subject to limited attention bias. This measure captures both purchases and sales, as attention affects selling decisions as well as buying decisions.

The disposition effect refers to investors' tendency to sell winning investments too early while holding losing investments too long (Kahneman & Tversky, 1979; Odean, 1998; Shefrin & Statman, 1985). Following Odean (1998), we compute the proportion of gains realized (PGR) and proportion of losses realized (PLR)

$$\text{PGR}_{it} = \frac{\text{Realized Gains}_{it}}{\text{Realized Gains}_{it} + \text{Paper Gains}_{it}}, \tag{34}$$

$$\text{PLR}_{it} = \frac{\text{Realized Losses}_{it}}{\text{Realized Losses}_{it} + \text{Paper Losses}_{it}}. \tag{35}$$

Realized gains (losses) are the dollar value of positions sold at prices above (below) the investor's cost basis. Paper gains (losses) are the dollar value of unrealized gains (losses) on positions held at month end.

The disposition effect ratio is

$$\text{DE}_{it} = \text{PGR}_{it} - \text{PLR}_{it}. \tag{36}$$

Positive values indicate the disposition effect, meaning a tendency to sell winners and hold losers. A rational investor with no behavioural bias would have DE ≈ 0 after controlling for tax considerations. Values substantially above zero indicate loss aversion consistent with prospect theory (Benartzi & Thaler, 1995; Kahneman & Tversky, 1979).

Extrapolation bias captures investors' tendency to chase recent returns by expecting past momentum to continue (Barberis et al., 2001; Greenwood & Shleifer, 2014). Following Hao et al. (2022), we measure extrapolation as the fraction of trades directed to momentum funds.

Momentum funds are defined as funds that performed in the top 10 percent of their style category over the prior 12 months. The extrapolation measure is

$$\text{Extrapolation}_{it} = \frac{\sum_{f \in \text{Momentum}} |\text{Trades}_{ift}|}{\sum_{f} |\text{Trades}_{ift}|}. \tag{37}$$

Higher values indicate stronger return-chasing behavior. This bias connects to broader evidence on investor expectations and belief formation (Gennaioli et al., 2018; Malmendier & Nagel, 2011).

Gambling bias, also known as lottery preference or tail return overweighting, reflects investors'

tendency to prefer assets with positively skewed returns that offer small probabilities of extreme gains (Kumar, 2009). Following Hao et al. (2022), we classify funds as lottery-like based on three characteristics.

A fund is classified as lottery-type if it simultaneously meets the following criteria. The fund price falls in the bottom quintile of all funds. The fund's idiosyncratic volatility, measured as the residual from a factor model, falls in the top quintile. The fund's idiosyncratic skewness falls in the top quintile.

These characteristics identify funds that resemble lottery tickets by offering low prices, high volatility, and the potential for extreme positive returns. Gambling bias is the share of trading value in lottery-type funds

$$\text{Gambling}_{it} = \frac{\sum_{f \in \text{Lottery}} |\text{Trades}_{ift}|}{\sum_{f} |\text{Trades}_{ift}|}. \tag{38}$$

Higher values indicate stronger lottery preferences. This bias is particularly relevant for understanding retail investor behavior (Barber et al., 2022).

Anchoring bias refers to investors' overreliance on salient reference points when making financial decisions. We propose a new measure based on trading activity near 52-week price extremes.

A trade is classified as anchored if it is executed when the fund price is within plus or minus 10 percent of its 12-month high or low price. The intuition is that investors use recent price peaks and troughs as reference points, leading them to perceive funds trading near their highs as expensive and funds trading near their lows as cheap regardless of fundamental value.

Anchoring bias is the share of trading value in anchored trades

$$\text{Anchoring}_{it} = \frac{\sum_{f \in \text{Anchored}} |\text{Trades}_{ift}|}{\sum_{f} |\text{Trades}_{ift}|}. \tag{39}$$

Higher values indicate stronger reliance on price reference points. This measure complements existing evidence on reference dependence in financial decisions (Barberis et al., 2001; Kahneman & Tversky, 1984).

Trading activity provides a measure of overconfidence, as overconfident investors trade more than warranted by their information (Barber & Odean, 2000, 2001; Grinblatt & Keloharju, 2009).

Total turnover is computed as

$$\text{Total Turnover}_{it} = \frac{1}{2} \times \frac{\text{Trade Value}_{it}}{\sum_{\tau=t-12}^{t-1} \text{Holdings}_{i\tau}/12}. \tag{40}$$

The factor of one-half avoids double-counting purchases and sales.

Speculative turnover isolates trading motivated by potentially misguided beliefs about short-term price movements. Following Barber and Odean (2002), we classify trades as speculative if they involve position reductions following prior-month gains

$$\text{Speculative Turnover}_{it} = \frac{1}{2} \times \frac{\text{Speculative Trade Value}_{it}}{\sum_{\tau=t-12}^{t-1} \text{Holdings}_{i\tau}/12}. \tag{41}$$

Specifically, we classify all profitable sales of complete positions followed by a purchase within one month as speculative, and all purchases made within one month of a speculative sale as speculative.

Higher turnover indicates greater overconfidence.

The return gap between self-directed and robo-advised portfolios captures relative performance and plays a central role in our analysis of learning and dynamic delegation.

The market return gap uses a common robo benchmark

$$\mathrm{RRG}_{it}^{\mathrm{market}} = \ln(1 + r_{it}^{\mathrm{Fund}}) - \ln(1 + r_{t}^{\mathrm{RA,market}}). \tag{42}$$

The individual return gap uses the investor's own robo return

$$\mathrm{RRG}_{it}^{\mathrm{own}} = \ln(1 + r_{it}^{\mathrm{Fund}}) - \ln(1 + r_{it}^{\mathrm{RA,own}}). \tag{43}$$

We decompose the return gap into positive and negative components to test for asymmetric responses

$$\mathrm{RRG}_{it}^{+} = \max\{\mathrm{RRG}_{it}, 0\} \quad \text{(self-directed outperforms)}, \tag{44}$$

$$\mathrm{RRG}_{it}^{-} = \min\{\mathrm{RRG}_{it}, 0\} \quad \text{(robo outperforms)}. \tag{45}$$

This decomposition allows us to test whether investors respond differently to outperformance versus underperformance of their self-directed portfolios, consistent with asymmetric updating predicted by models of motivated reasoning (Gervais & Odean, 2001).

All continuous variables are standardized within each month to mean zero and unit standard deviation prior to estimation. This facilitates coefficient comparability across variables and over time, and ensures that coefficients represent the effect of a one-standard-deviation change in each characteristic (Chetty, 2009).

A1.4. Data Moments

Table A3: Fama–MacBeth Averaged Monthly Moments of RA Adoption and Allocation

	Adoption Indicator		Allocation Share	
Sample	Mean	SD	Mean	SD
Panel A: Participation Margins				
General	0.321	0.456	0.102	0.158
First Use	0.014	0.107	0.108	0.163
Continuation	0.304	0.443	0.101	0.157
Re-entry	0.002	0.043	0.153	0.214
Panel B: Heterogeneity by Age				
Top 25% (Oldest)	0.344	0.457	0.083	0.139
Bottom 25% (Youngest)	0.275	0.438	0.128	0.181
Panel C: Heterogeneity by Wealth				
Top 25% (Wealthiest)	0.433	0.483	0.066	0.110
Bottom 25% (Least Wealthy)	0.169	0.358	0.227	0.228
Panel D: Heterogeneity by Limited Attention				
Top 25% (Most Inattentive)	0.294	0.444	0.110	0.168

Continued on next page

Table A3 (continued)

	Adoption Indicator		Allocation Share	
Sample	Mean	SD	Mean	SD
Bottom 25% (Most Attentive)	0.304	0.447	0.120	0.175
Panel E: Heterogeneity by Timing Skill				
Top 25% (Highest Skill)	0.309	0.454	0.112	0.160
Bottom 25% (Lowest Skill)	0.320	0.456	0.096	0.158
Panel F: Heterogeneity by Underdiversification				
Top 25% (Most Concentrated)	0.180	0.375	0.188	0.244
Bottom 25% (Most Diversified)	0.449	0.484	0.073	0.110
Panel G: Comparison with Automated Trading				
	Adoption Indicator		Allocation Share	
Product	Mean	SD	Mean	SD
Robo-Advising (d_{it}, s_{it})	0.321	0.456	0.102	0.158
Automated Trading (a_{it}, a_{it}^{share})	0.329	0.470	0.037	0.065

Notes. Entries report Fama–MacBeth averages of monthly cross-sectional moments (each month equally weighted). Adoption Indicator Mean is the monthly adoption rate averaged across months; SD is the average monthly cross-sectional standard deviation. For First Use, Continuation, and Re-entry rows, moments are computed from the corresponding event indicators using the full monthly sample as denominator. Allocation Share moments are computed conditional on adoption (or conditional on the relevant event subsample for participation margin rows). Top and bottom groups are defined each month using within-month 25th and 75th percentiles of the heterogeneity variable. Panel G compares robo-advising with automated trading (rule-based periodic contributions to self-selected funds). For robo-advising, $d_{it} = 1$ if investor i holds any robo-advised position in month t, and s_{it} is the share of mutual fund wealth allocated to robo-advising conditional on $d_{it} = 1$. For automated trading, $a_{it} = 1$ if investor i uses automated trading in month t, and a_{it}^{share} is the share of mutual fund wealth subject to automated contributions conditional on $a_{it} = 1$.

A1.5. Robustness Checks: Heterogeneity Analysis

This section examines whether the determinants of adoption and delegation vary systematically across investor subgroups. We partition the sample along five dimensions and estimate separate Heckman models for the top and bottom quartiles of each. For age, we compare investors in the oldest quartile against those in the youngest quartile. For wealth, we compare the wealthiest quartile against the least wealthy. For timing skill, we compare the highest-skill quartile against the lowest-skill quartile. For underdiversification, we compare the most concentrated quartile against the most diversified. For limited attention, we compare the most inattentive quartile against the most attentive (lowest limited attention bias). In each case, estimating the model separately for the two extreme quartiles allows us to assess whether the mechanisms documented in the full sample operate uniformly or are concentrated among particular investor types. Tables A5 through A8 report the results.

Older investors adopt at higher rates (34.4% versus 27.5%) but delegate less conditional on adoption (8.27% versus 12.76%).[19]

Among older investors, wealth increases adoption by 2.7 percentage points and reduces delegation by 1.8% of the mean.[20] Among the young, the picture is strikingly different. Wealth increases adoption

[19] Sample moments for the oldest quartile are $p_0 = 0.344$, $\phi(z_0) = 0.366$, mean delegation = 8.27%, and SD = 13.88%. For the youngest quartile the corresponding values are $p_0 = 0.275$, $\phi(z_0) = 0.335$, mean delegation = 12.76%, and SD = 18.09%.

[20] Oldest quartile effects: adoption, $0.366 \times 0.073 \approx 0.027$; delegation, $0.011 \times 0.1388/0.0827 \approx 0.018$.

by 15.0 percentage points and *increases* delegation by 8.2% of the mean.[21] This opposite sign indicates that wealth proxies for sophistication-induced caution among the old but enables aggressive delegation among the young, consistent with lifecycle models of risk-taking (Cocco, 2005).

Prior experience on other robo platforms also behaves differently across age groups. Among older investors, prior experience reduces delegation by 6.4% of the mean, while among younger investors it increases delegation by 32.8% of the mean.[22] Older investors diversify their commitments across platforms. Younger investors concentrate.

The delegation effect of fund trading experience is driven entirely by the older group, who reduce delegation by 59.4% of the mean.[23] Experienced older investors have accumulated human capital over decades that is costly to cede, and they behave accordingly. Younger investors show no significant delegation response to fund trading experience.

The underdiversification opposite sign operates among older investors, increasing delegation by 6.5% of the mean, but is absent among the young.[24] The awareness updating mechanism thus operates primarily among older concentrated investors who discover diversification benefits upon adoption (Kumar, 2009).

The inverse Mills ratio is large and consistently positive among younger investors, ranging from 67% to 108% of the mean across specifications, but small and inconsistently signed among older investors. Selection on unobserved match quality is far stronger among the young.

The overall picture that emerges is one of functional differentiation. Young investors exhibit large effects and strong selection, treating robo-advising as a vehicle for risk-taking. Older investors exhibit opposite signs for experience and underdiversification, treating robo-advising as a diversification tool (Agarwal et al., 2009).

Wealthy investors adopt at much higher rates (43.3% versus 16.9%) but delegate far less conditional on adoption (6.57% versus 22.66%).[25]

Among the wealthy, age has no adoption effect but reduces delegation by 1.5% of the mean. Among the less wealthy, age increases adoption by 2.0 percentage points with no delegation effect.[26] The age-adoption relationship operates only among less wealthy investors, who may view robo-advising as a low-cost entry point to professional portfolio management.

The experience-delegation tradeoff is confined to the wealthy, who reduce delegation by 44.3% of the mean.[27] Wealthy investors have accumulated substantial human capital in active management. Less wealthy investors face lower opportunity costs of delegation and show no significant effect.

Timing skill produces a opposite sign across wealth groups. Among the wealthy, higher timing scores increase delegation by 1.2% of the mean. Among the less wealthy, timing skill reduces delegation by 1.6% of the mean.[28] Wealthy skilled investors use robo-advising as a complement to their

[21] Youngest quartile effects: adoption, $0.335 \times 0.448 \approx 0.150$; delegation, $0.058 \times 0.1809/0.1276 \approx 0.082$.

[22] Oldest quartile: $0.038 \times 0.1388/0.0827 \approx 0.064$. Youngest quartile: $0.231 \times 0.1809/0.1276 \approx 0.328$.

[23] Oldest quartile: $0.354 \times 0.1388/0.0827 \approx 0.594$.

[24] Oldest quartile: $0.039 \times 0.1388/0.0827 \approx 0.065$.

[25] Sample moments for the wealthiest quartile are $p_0 = 0.433$, $\phi(z_0) = 0.392$, mean delegation = 6.57%, and SD = 11.03%. For the least wealthy quartile the corresponding values are $p_0 = 0.169$, $\phi(z_0) = 0.249$, mean delegation = 22.66%, and SD = 22.75%.

[26] Wealthiest quartile: $0.009 \times 0.1103/0.0657 \approx 0.015$. Least wealthy quartile: $0.249 \times 0.079 \approx 0.020$.

[27] Wealthiest quartile: $0.264 \times 0.1103/0.0657 \approx 0.443$.

[28] Wealthiest quartile: $0.007 \times 0.1103/0.0657 \approx 0.012$. Least wealthy quartile: $0.016 \times 0.2275/0.2266 \approx 0.016$.

existing strategies. Less wealthy skilled investors avoid it, preferring to preserve active discretion over the larger share of their portfolio that robo-advising would command.

The underdiversification opposite sign operates among the wealthy, increasing delegation by 7.9% of the mean, but is absent among the less wealthy.[29] The awareness mechanism thus operates primarily among wealthy investors who respond to diversification benefits. Less wealthy concentrated investors may face binding liquidity or information constraints rather than correctable bias.

The inverse Mills ratio is negative among the wealthy (-12.1% of the mean), indicating that wealthy marginal adopters are experimenters who delegate tentatively.[30] Selection is insignificant among the less wealthy.

The contrast is sharp. Wealthy investors adopt at high rates but delegate cautiously. Less wealthy investors adopt at lower rates but delegate substantially. Robo-advising functions as a marginal tool for the wealthy and a primary investment vehicle for the less wealthy (Philippon, 2019).

Adoption rates are similar across skill groups (30.9% versus 32.0%), but high-skill investors delegate slightly more conditional on adoption (11.16% versus 9.65%).[31]

The age-delegation opposite sign operates only among high-skill investors, who reduce delegation by 3.9% of the mean.[32] Older skilled investors have accumulated expertise that is costly to cede. Older investors with low timing skill have less to lose from delegation and show no significant effect.

Among low-skill investors, prior experience on other robo platforms increases delegation by 13.3% of the mean.[33] Low-skill investors with prior experience appear to learn that robo-advising provides value they cannot replicate on their own. High-skill investors show no significant delegation response.

Among high-skill investors, higher timing scores reduce adoption but increase delegation by 10.3% of the mean.[34] The most skilled timers who do choose robo-advising commit to it substantially, suggesting genuine complementarity between personal timing ability and algorithmic portfolio construction.

The underdiversification opposite sign operates among high-skill investors, increasing delegation by 7.8% of the mean, but is absent among the low-skill group.[35]

The inverse Mills ratio is much larger among low-skill investors (68.3% of the mean) than high-skill investors (19.1%).[36] Low-skill adopters who overcome observable barriers reveal strong unobserved affinity for algorithmic delegation, consistent with recognition of their own limitations.

The pattern that emerges is one of functional differentiation. Skilled investors use robo-advising selectively as a complement to active management. Unskilled investors use it as a substitute for inadequate self-management (Gârleanu & Pedersen, 2018). Concentrated investors adopt at much lower rates (17.96% versus 44.85%) but delegate far more conditional on adoption (18.80% versus 7.29%).[37]

[29] Wealthiest quartile: $0.047 \times 0.1103/0.0657 \approx 0.079$.

[30] Wealthiest quartile: $0.072 \times 0.1103/0.0657 \approx 0.121$.

[31] Sample moments for high timing skill investors are $p_0 = 0.309$, $\phi(z_0) = 0.350$, mean delegation = 11.16%, and SD = 16.03%. For low timing skill the corresponding values are $p_0 = 0.320$, $\phi(z_0) = 0.357$, mean delegation = 9.65%, and SD = 15.83%.

[32] High-skill: $0.027 \times 0.1603/0.1116 \approx 0.039$.

[33] Low-skill: $0.081 \times 0.1583/0.0965 \approx 0.133$.

[34] High-skill: $0.072 \times 0.1603/0.1116 \approx 0.103$.

[35] High-skill: $0.054 \times 0.1603/0.1116 \approx 0.078$.

[36] Low-skill: $0.416 \times 0.1583/0.0965 \approx 0.683$. High-skill: $0.133 \times 0.1603/0.1116 \approx 0.191$.

[37] Sample moments for the most concentrated quartile are $p_0 = 0.180$, $\phi(z_0) = 0.263$, mean delegation = 18.80%, and SD = 24.37%. For the most diversified quartile the corresponding values are $p_0 = 0.449$, $\phi(z_0) = 0.396$, mean delegation

This unconditional contrast already foreshadows the within-group patterns.

Wealth facilitates adoption more strongly among concentrated investors (5.6 pp versus 2.0 pp).[38] Wealthy concentrated investors command greater resources to explore alternatives to their existing holdings. Liquidity reduces delegation by 9.5% of the mean among concentrated investors versus just 2.4% among diversified investors.[39] Concentrated investors with high liquidity preferences maintain flexibility for the active trading they are accustomed to. The experience-delegation effect is driven entirely by concentrated investors, who reduce delegation by 29.4% of the mean.[40] Experienced concentrated investors have accumulated expertise in their specific holdings and are reluctant to relinquish it. Diversified investors show no significant effect.

The within-group underdiversification effect is revealing. Among concentrated investors, higher underdiversification increases delegation by 22.2% of the mean. Among diversified investors, the effect is 7.7%.[41] The opposite sign is roughly three times larger among concentrated investors. This provides strong support for the awareness updating mechanism. The most concentrated investors who adopt discover diversification benefits that are most salient relative to their prior portfolios (Goetzmann & Kumar, 2008).

Adoption rates and delegation intensities are similar across attention groups (29.4% versus 30.4% in adoption; 10.99% versus 11.98% in delegation).[42] Investors with lower limited attention show larger delegation effects from risk tolerance (4.1% versus 2.9% of the mean).[43] Attention enables investors to act on their risk preferences. Those who are inattentive cannot fully translate risk appetite into delegation decisions.

The underdiversification opposite sign operates only among limited attentive investors, increasing delegation by 2.9% of the mean.[44] Inattentive concentrated investors are the most likely to be unaware of their bias ex ante. Adoption reveals diversification benefits that attentive investors may already recognize, limiting the scope for belief updating among the attentive group. Among inattentive investors, higher attention bias reduces adoption but increases delegation by 2.9% of the mean, mirroring the underdiversification pattern. Robo-advising substitutes for the monitoring capacity these investors cannot provide on their own. Attentive investors show larger effects for risk tolerance and gender. Inattentive investors show the underdiversification opposite sign. Robo-advising serves as a substitute for attention among the inattentive and as a complement to active decision-making among the attentive (Barber & Odean, 2008).

Table A9 summarizes the key patterns across the five heterogeneity dimensions.

Three patterns emerge consistently across the heterogeneity dimensions.

First, opposite signs and awareness updating operate selectively. The underdiversification opposite sign appears among older, wealthier, more skilled, and limited attentive investors. These are the

= 7.29%, and SD = 11.02%.

[38] Concentrated: $0.263 \times 0.211 \approx 0.056$. Diversified: $0.396 \times 0.051 \approx 0.020$.

[39] Concentrated: $0.073 \times 0.2437/0.1880 \approx 0.095$. Diversified: $0.016 \times 0.1102/0.0729 \approx 0.024$.

[40] Concentrated: $0.227 \times 0.2437/0.1880 \approx 0.294$.

[41] Concentrated: $0.171 \times 0.2437/0.1880 \approx 0.222$. Diversified: $0.051 \times 0.1102/0.0729 \approx 0.077$.

[42] Sample moments for the high limited attention group are $p_0 = 0.294$, $\phi(z_0) = 0.345$, mean delegation = 10.99%, and SD = 16.82%. For the low limited attention group the corresponding values are $p_0 = 0.304$, $\phi(z_0) = 0.351$, mean delegation = 11.98%, and SD = 17.49%.

[43] Low attention bias: $0.028 \times 0.1749/0.1198 \approx 0.041$. High attention bias: $0.019 \times 0.1682/0.1099 \approx 0.029$.

[44] High attention bias: $0.019 \times 0.1682/0.1099 \approx 0.029$.

groups most likely to be unaware of their biases ex ante and to update beliefs upon experiencing robo-advising. The mechanism requires both a correctable bias and scope for learning, conditions that are not uniformly satisfied across the investor population.

Second, selection on unobservables varies systematically. Selection is strong among younger and less skilled investors who reveal unobserved affinity for robo-advising by overcoming observable barriers. Selection is weak or negative among older and wealthier investors who adopt for more heterogeneous and often experimental reasons.

Third, robo-advising serves fundamentally different functions across investor types. For young, less wealthy, and less skilled investors, it operates as a primary vehicle for market participation. For older, wealthier, and more skilled investors, it functions as a marginal complement to existing strategies. Understanding these distinct roles is essential for interpreting both the cross-sectional patterns documented in earlier sections and the welfare implications of expanding access to algorithmic advice.

Table A4: Demographics, Skills, and Behavioural Biases for Heterogeneity Analysis by Wealth

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
A. Top 25% Wealth Sample						
Constant	-0.544***	0.211***	-0.229	0.029	-1.224***	0.210***
	(-5.300)	(13.038)	(-1.562)	(0.180)	(-6.084)	(5.047)
Total Financial Assets$_{t-1}$	0.038***	-0.006***	0.032***	-0.006***	0.025***	-0.003***
	(10.776)	(-8.026)	(9.590)	(-6.268)	(9.819)	(-4.479)
Risk Preference	0.107***	-0.002	0.089***	-0.004	0.099***	0.003*
	(9.788)	(-1.564)	(7.368)	(-1.448)	(9.979)	(1.872)
Age	-0.005	-0.009***	-0.013	-0.005***	-0.003	-0.011***
	(-0.328)	(-8.061)	(-0.973)	(-3.551)	(-0.194)	(-6.738)
Gender	-0.105***	-0.006***	-0.102***	-0.001	-0.131***	-0.006***
	(-7.274)	(-5.669)	(-7.385)	(-0.328)	(-11.666)	(-2.898)
Combined RA Dummy$_{t-1}$	0.602***	-0.067***	0.578***	-0.084***	0.527***	-0.034***
	(25.952)	(-14.450)	(26.466)	(-11.884)	(24.350)	(-6.990)
Baby Assets$_{t-1}$	-0.053***	-0.006***	-0.042***	-0.005***	-0.035***	-0.010***
	(-11.696)	(-5.391)	(-11.569)	(-5.090)	(-10.378)	(-6.473)
Experience of Fund Trading$_{t-1}$			0.501***	-0.264**		
			(4.627)	(-2.392)		
Selection Score$_{t-1}$			0.017*	0.001		
			(1.710)	(0.434)		
Timing Score (0-100)$_{t-1}$			0.020**	0.007***		
			(2.558)	(4.796)		
Underdiversification$_{t-1}$					-0.191***	0.047***
					(-18.237)	(12.513)
Limited Attention Bias$_{t-1}$					-0.047***	-0.003
					(-7.516)	(-1.634)
Disposition Effect Ratio$_{t-1}$					-5.714	-0.353
					(-1.246)	(-0.309)
Extrapolation Bias$_{t-1}$					0.011**	-0.001
					(2.214)	(-0.617)
Gambling Bias$_{t-1}$					-0.053	-0.005
					(-1.443)	(-0.408)
Anchoring Bias$_{t-1}$					-0.031	0.021
					(-1.032)	(1.628)
Total Turnover$_{t-1}$					-64.005***	5.678***
					(-3.010)	(2.885)
Speculative Turnover$_{t-1}$					-20.682	-11.996***
					(-1.494)	(-6.589)
Length of Registration$_{t-1}$	0.059***		0.051***		0.056***	
	(8.310)		(7.483)		(7.848)	
Inverse Mills Ratio		-0.072***		-0.142***		-0.017
		(-7.153)		(-9.105)		(-1.285)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.042	0.015	0.046	0.022	0.059	0.036
N	1,174,272	519,312	1,157,904	518,688	1,174,272	519,312
B. Bottom 25% Wealth Sample						
Constant	16.170***	3.095	12.877***	-3.024*	12.560***	-2.936
	(5.364)	(0.579)	(5.448)	(-1.831)	(6.785)	(-1.418)

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Table A4 (continued)

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Total Financial Assets$_{t-1}$	57.805***	14.800	47.421***	-7.115	44.495***	-7.849
	(5.291)	(0.744)	(4.905)	(-1.137)	(6.867)	(-1.007)
Risk Preference	0.024	0.007	0.009	0.005	0.022	-0.001
	(1.597)	(0.481)	(0.655)	(0.568)	(1.567)	(-0.075)
Age	0.079***	-0.017	0.077***	-0.011	0.092***	-0.016
	(4.279)	(-1.048)	(4.551)	(-0.894)	(6.793)	(-1.621)
Gender	-0.133***	-0.017	-0.128***	0.003	-0.141***	0.005
	(-21.771)	(-0.718)	(-26.582)	(0.121)	(-20.181)	(0.238)
Combined RA Dummy$_{t-1}$	0.486***	-0.015	0.472***	-0.018	0.446***	-0.041
	(9.898)	(-0.205)	(11.904)	(-0.262)	(16.337)	(-0.664)
Baby Assets$_{t-1}$	-13.275***	-9.188	-10.497***	-3.197**	-9.150***	-3.047**
	(-4.087)	(-1.602)	(-3.492)	(-2.522)	(-5.874)	(-2.025)
Experience of Fund Trading$_{t-1}$			-0.212	-0.068		
			(-1.004)	(-1.244)		
Selection Score$_{t-1}$			0.004	-0.003		
			(1.388)	(-1.027)		
Timing Score (0-100)$_{t-1}$			-0.026*	-0.016***		
			(-1.699)	(-2.909)		
Underdiversification$_{t-1}$					-0.185***	0.030
					(-15.434)	(1.433)
Limited Attention Bias$_{t-1}$					-0.033***	0.016
					(-5.619)	(1.330)
Disposition Effect Ratio$_{t-1}$					-0.689	10.422
					(-0.882)	(0.989)
Extrapolation Bias$_{t-1}$					-0.010***	-0.008***
					(-3.239)	(-3.123)
Gambling Bias$_{t-1}$					0.005	-0.027
					(1.042)	(-1.154)
Anchoring Bias$_{t-1}$					0.038*	0.018**
					(1.884)	(2.501)
Total Turnover$_{t-1}$					-0.544**	0.402*
					(-2.298)	(1.846)
Speculative Turnover$_{t-1}$					-12.086***	-2.391
					(-4.464)	(-0.917)
Length of Registration$_{t-1}$	-0.013***		-0.014***		0.001	
	(-3.941)		(-4.185)		(0.106)	
Inverse Mills Ratio		0.207		0.086		0.015
		(0.972)		(0.467)		(0.077)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.065	0.059	0.028	0.071	0.080	0.075
N	1,160,496	202,992	952,176	200,832	1,118,306	202,992

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel A: Oldest 25% sample (T=48 for Panels 1-2, T=46 for Panel 3 Probit, T=48 for Panel 3 Outcome). Panel B: Youngest 25% sample (T=48 for all panels). Panel 1 includes baseline controls, Panel 2 includes experience, selection, and timing score variables, and Panel 3 includes comprehensive behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A5: Demographics, Skills, and Behavioural Biases for Heterogeneity Analysis by Age

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=46-48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
A. Top 25% (Oldest) Age Sample						
Constant	-0.730***	0.064	-0.352	-0.062	-3.780	0.203*
	(-6.199)	(1.497)	(-1.292)	(-0.242)	(-1.396)	(1.804)
Total Financial Assets$_{t-1}$	0.073***	-0.011***	0.059***	-0.014***	0.030***	-0.006***
	(7.058)	(-10.252)	(6.468)	(-16.340)	(4.599)	(-5.578)
Risk Preference	0.090***	0.007**	0.070***	0.001	0.065***	0.011***
	(6.186)	(2.231)	(4.598)	(0.506)	(5.229)	(3.708)
Age	0.021*	-0.006**	0.015	-0.005***	0.015*	-0.005**
	(1.835)	(-2.566)	(1.366)	(-3.513)	(1.784)	(-2.132)
Gender	-0.106***	-0.004*	-0.103***	0.006**	-0.121***	-0.006*
	(-11.258)	(-1.708)	(-10.749)	(2.551)	(-18.250)	(-1.802)
Combined RA Dummy$_{t-1}$	0.725***	-0.038***	0.669***	-0.092***	0.603***	-0.006
	(33.820)	(-3.430)	(31.296)	(-6.040)	(38.691)	(-0.685)
Baby Assets$_{t-1}$	-0.039***	-0.011***	-0.033***	-0.009***	-0.030***	-0.013***
	(-13.719)	(-5.307)	(-12.309)	(-3.918)	(-7.980)	(-5.577)
Experience of Fund Trading$_{t-1}$			0.473***	-0.354**		
			(2.670)	(-2.297)		
Selection Score$_{t-1}$			0.004	-0.002*		
			(0.800)	(-1.693)		
Timing Score$_{t-1}$			-0.009	0.004		
			(-1.094)	(0.940)		
Underdiversification$_{t-1}$					-0.240***	0.039***
					(-16.686)	(8.041)
Limited Attention Bias$_{t-1}$					-0.042***	0.002
					(-5.804)	(1.474)
Disposition Effect Ratio$_{t-1}$					-13.465	12.737
					(-1.344)	(1.348)
Extrapolation Bias$_{t-1}$					0.003	-0.005***
					(0.561)	(-4.031)
Gambling Bias$_{t-1}$					-19.239	-0.007**
					(-1.013)	(-2.372)
Anchoring Bias$_{t-1}$					-0.007	0.012*
					(-0.244)	(1.766)
Total Turnover$_{t-1}$					-41.042***	3.596**
					(-2.723)	(2.155)
Speculative Turnover$_{t-1}$					-4.894	-4.563**
					(-0.758)	(-2.401)
Length of Registration$_{t-1}$	0.060***		0.047***		0.057***	
	(14.871)		(11.208)		(13.562)	
Inverse Mills Ratio		0.065**		-0.086**		0.111***
		(2.025)		(-2.076)		(3.311)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.047	0.022	0.046	0.043	0.075	0.056
N	1,324,560	464,544	1,249,392	463,680	1,269,876	464,544
B. Bottom 25% (Youngest) Age Sample						
Constant	-0.827***	-0.759***	-0.681***	-1.187***	-1.455***	-0.535***
	(-14.366)	(-6.442)	(-4.502)	(-3.749)	(-2.843)	(-6.981)

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Table A5 (continued)

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=46-48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Total Financial Assets$_{t-1}$	0.448***	0.058***	0.362***	0.065***	0.241***	0.028***
	(9.751)	(5.442)	(10.949)	(5.238)	(5.953)	(3.467)
Risk Preference	0.119***	0.060***	0.090***	0.061***	0.108***	0.039***
	(6.864)	(5.940)	(5.834)	(6.241)	(7.558)	(6.229)
Age	0.005	-0.078***	-0.034	-0.093***	-0.009	-0.102***
	(0.105)	(-9.225)	(-0.706)	(-11.985)	(-0.223)	(-17.843)
Gender	-0.075***	-0.049***	-0.083***	-0.059***	-0.130***	-0.040***
	(-5.615)	(-7.400)	(-6.919)	(-6.734)	(-16.847)	(-8.475)
Combined RA Dummy$_{t-1}$	0.750***	0.231***	0.693***	0.270***	0.614***	0.124***
	(26.561)	(5.129)	(24.737)	(5.008)	(27.653)	(6.288)
Baby Assets$_{t-1}$	-0.130***	-0.085***	-0.102***	-0.087***	-0.068***	-0.075***
	(-8.438)	(-4.762)	(-8.324)	(-4.604)	(-4.049)	(-4.223)
Experience of Fund Trading$_{t-1}$			0.248***	-0.169		
			(2.730)	(-0.895)		
Selection Score$_{t-1}$			0.016***	0.007*		
			(2.600)	(1.689)		
Timing Score$_{t-1}$			-0.011	0.006		
			(-1.318)	(1.304)		
Underdiversification$_{t-1}$					-0.265***	-0.010
					(-20.900)	(-1.078)
Limited Attention Bias$_{t-1}$					-0.048***	-0.015***
					(-6.976)	(-3.794)
Disposition Effect Ratio$_{t-1}$					-0.636	-0.566**
					(-1.344)	(-2.420)
Extrapolation Bias$_{t-1}$					0.006	-0.002
					(1.619)	(-1.491)
Gambling Bias$_{t-1}$					-3.240	-0.002
					(-1.011)	(-0.657)
Anchoring Bias$_{t-1}$					0.005	0.005
					(0.150)	(0.611)
Total Turnover$_{t-1}$					-11.268***	-0.081
					(-3.209)	(-0.164)
Speculative Turnover$_{t-1}$					-33.516***	-12.658**
					(-5.027)	(-2.285)
Length of Registration$_{t-1}$	0.013***		0.001		0.025***	
	(2.732)		(0.300)		(7.596)	
Inverse Mills Ratio		0.644***		0.764***		0.472***
		(8.545)		(7.762)		(11.046)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.046	0.042	0.042	0.052	0.081	0.081
N	1,251,792	349,536	1,143,456	348,144	1,251,792	349,536

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel A: Oldest 25% sample (T=48 for Panels 1-2, T=46 for Panel 3 Probit, T=48 for Panel 3 Outcome). Panel B: Youngest 25% sample (T=48 for all panels). Panel 1 includes baseline controls, Panel 2 includes experience, selection, and timing score variables, and Panel 3 includes comprehensive behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A6: Demographics, Skills, and Behavioural Biases for Heterogeneity Analysis by Timing Skill

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=46-48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
A. Top 25% Timing Skill Sample						
Constant	-0.808***	0.019	-0.347	-0.333	-3.156	0.177***
	(-9.963)	(0.502)	(-1.610)	(-1.363)	(-1.618)	(2.746)
Total Financial Assets$_{t-1}$	0.121***	-0.016***	0.104***	-0.013***	0.081***	-0.013***
	(8.841)	(-5.547)	(8.515)	(-7.318)	(6.700)	(-2.595)
Risk Preference	0.124***	0.014***	0.115***	0.014***	0.113***	0.014***
	(18.393)	(6.278)	(15.082)	(5.758)	(12.175)	(4.563)
Age	0.055***	-0.027***	0.048***	-0.027***	0.056***	-0.028***
	(3.748)	(-8.212)	(3.410)	(-8.878)	(3.604)	(-9.274)
Gender	-0.150***	-0.012***	-0.149***	-0.009**	-0.166***	-0.001
	(-30.422)	(-2.731)	(-29.926)	(-2.165)	(-21.283)	(-0.236)
Combined RA Dummy$_{t-1}$	0.689***	-0.012	0.660***	-0.020**	0.628***	-0.018
	(26.257)	(-1.402)	(28.069)	(-2.527)	(27.631)	(-1.606)
Baby Assets$_{t-1}$	-0.048***	-0.030***	-0.042***	-0.031***	-0.026***	-0.031***
	(-8.756)	(-7.859)	(-8.527)	(-7.684)	(-3.086)	(-6.915)
Experience of Fund Trading$_{t-1}$			0.175*	-0.236*		
			(1.853)	(-1.700)		
Selection Score$_{t-1}$			0.014***	-0.002		
			(2.765)	(-0.872)		
Timing Score$_{t-1}$			-0.391***	0.072***		
			(-10.589)	(10.886)		
Underdiversification$_{t-1}$					-0.197***	0.054***
					(-13.692)	(10.875)
Limited Attention Bias$_{t-1}$					-0.024***	0.003
					(-3.376)	(0.591)
Disposition Effect Ratio$_{t-1}$					-0.738	-1.233
					(-1.414)	(-1.159)
Extrapolation Bias$_{t-1}$					-0.016***	-0.005
					(-3.305)	(-1.225)
Gambling Bias$_{t-1}$					-14.999	-0.006***
					(-1.088)	(-3.144)
Anchoring Bias$_{t-1}$					0.070***	0.017
					(7.352)	(1.598)
Total Turnover$_{t-1}$					-38.117***	14.902***
					(-3.658)	(3.505)
Speculative Turnover$_{t-1}$					-36.128***	-4.322
					(-2.921)	(-0.469)
Length of Registration$_{t-1}$	0.068***		0.063***		0.072***	
	(15.759)		(14.609)		(15.195)	
Inverse Mills Ratio		0.133***		0.105***		0.087**
		(4.209)		(3.488)		(2.434)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.042	0.029	0.050	0.041	0.061	0.074
N	1,063,920	341,136	1,063,920	341,136	498,768	155,328
B. Bottom 25% Timing Skill Sample						
Constant	-0.689***	-0.277***	-1.711	-0.809*	16.294	-949.103
	(-5.064)	(-3.751)	(-1.394)	(-1.804)	(0.419)	(-0.629)

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Table A6 (continued)

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=46-48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Total Financial Assets$_{t-1}$	0.073***	0.002	0.070***	0.002	0.033***	-0.003
	(7.042)	(0.555)	(6.869)	(0.512)	(3.467)	(-1.382)
Risk Preference	0.067***	0.008*	0.055**	0.006	0.051**	0.012**
	(2.642)	(1.817)	(2.042)	(1.465)	(2.231)	(2.387)
Age	0.052***	-0.005	0.048***	-0.004	0.052***	-0.009
	(5.811)	(-0.557)	(6.077)	(-0.452)	(5.022)	(-1.091)
Gender	-0.078***	-0.021***	-0.080***	-0.019***	-0.098***	-0.025***
	(-3.951)	(-5.355)	(-4.136)	(-5.662)	(-6.874)	(-5.881)
Combined RA Dummy$_{t-1}$	0.637***	0.081***	0.612***	0.074**	0.483***	0.045***
	(33.009)	(2.853)	(32.241)	(2.254)	(21.575)	(3.159)
Baby Assets$_{t-1}$	-0.026***	-0.017***	-0.025***	-0.017***	-0.023**	-0.023***
	(-3.555)	(-6.277)	(-3.411)	(-6.015)	(-2.542)	(-3.859)
Experience of Fund Trading$_{t-1}$			-0.579	-0.404		
			(-0.781)	(-1.469)		
Selection Score$_{t-1}$			-0.011***	-0.003		
			(-2.740)	(-1.436)		
Timing Score$_{t-1}$			0.148**	0.036***		
			(2.563)	(3.829)		
Underdiversification$_{t-1}$					-0.219***	0.010
					(-26.875)	(1.455)
Limited Attention Bias$_{t-1}$					-0.034***	-0.002
					(-5.672)	(-0.517)
Disposition Effect Ratio$_{t-1}$					1429.302	-79742.930
					(0.452)	(-0.639)
Extrapolation Bias$_{t-1}$					0.004	-0.004
					(0.627)	(-1.374)
Gambling Bias$_{t-1}$					-3.510	230.907
					(-1.123)	(1.114)
Anchoring Bias$_{t-1}$					0.005	0.013
					(0.374)	(1.482)
Total Turnover$_{t-1}$					-9.869*	3.130**
					(-1.902)	(2.486)
Speculative Turnover$_{t-1}$					-29.985***	0.303
					(-2.730)	(0.084)
Length of Registration$_{t-1}$	0.047***		0.041***		0.048***	
	(9.130)		(6.596)		(10.268)	
Inverse Mills Ratio		0.416***		0.401***		0.348***
		(4.958)		(4.127)		(6.826)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.041	0.038	0.046	0.047	0.067	0.095
N	1,062,240	353,520	1,062,240	353,520	487,061	172,032

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel A: Oldest 25% sample (T=48 for Panels 1-2, T=46 for Panel 3 Probit, T=48 for Panel 3 Outcome). Panel B: Youngest 25% sample (T=48 for all panels). Panel 1 includes baseline controls, Panel 2 includes experience, selection, and timing score variables, and Panel 3 includes comprehensive behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A7: Demographics, Skills, and Behavioural Biases for Heterogeneity Analysis by Underdiversification

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
A. Top 25% Underdiversification Sample						
Constant	-1.064***	-0.009	-1.132***	-0.078	-0.261***	-0.204***
	(-11.504)	(-0.131)	(-3.568)	(-0.467)	(-3.211)	(-3.222)
Total Financial Assets$_{t-1}$	0.211***	0.020	0.159***	0.009	0.178***	0.024*
	(5.344)	(1.636)	(5.540)	(1.049)	(4.831)	(1.872)
Risk Preference	0.081***	0.028***	0.060***	0.024***	0.075***	0.029***
	(5.551)	(5.895)	(4.498)	(10.087)	(5.445)	(5.833)
Age	0.059***	-0.031***	0.053***	-0.030***	0.055***	-0.033***
	(3.342)	(-7.159)	(3.359)	(-8.611)	(3.193)	(-7.485)
Gender	-0.115***	-0.013**	-0.111***	-0.007*	-0.114***	-0.013**
	(-19.254)	(-2.442)	(-14.859)	(-1.721)	(-19.413)	(-2.203)
Combined RA Dummy$_{t-1}$	0.640***	-0.026*	0.607***	-0.058***	0.602***	-0.027*
	(26.521)	(-1.698)	(25.708)	(-3.484)	(26.310)	(-1.730)
Baby Assets$_{t-1}$	-0.078***	-0.073***	-0.056***	-0.071***	-0.065***	-0.075***
	(-5.796)	(-4.981)	(-4.857)	(-5.255)	(-5.268)	(-5.085)
Experience of Fund Trading$_{t-1}$			-0.089	-0.227***		
			(-0.495)	(-2.609)		
Selection Score$_{t-1}$			0.001	-0.001		
			(0.757)	(-0.959)		
Timing Score$_{t-1}$			0.036***	-0.008		
			(4.517)	(-1.391)		
Underdiversification$_{t-1}$					-0.618***	0.171***
					(-13.098)	(7.347)
Limited Attention Bias$_{t-1}$					-0.035***	-0.003
					(-6.253)	(-1.188)
Disposition Effect Ratio$_{t-1}$					-0.109	-0.025
					(-1.303)	(-0.262)
Extrapolation Bias$_{t-1}$					-0.010***	-0.004*
					(-3.370)	(-1.862)
Gambling Bias$_{t-1}$					0.002	-0.001
					(0.724)	(-0.313)
Anchoring Bias$_{t-1}$					0.026	-0.002
					(1.286)	(-0.622)
Total Turnover$_{t-1}$					-0.788	0.129**
					(-1.549)	(2.475)
Speculative Turnover$_{t-1}$					-11.555**	-0.317
					(-2.342)	(-0.205)
Length of Registration$_{t-1}$	0.074***		0.064***		0.067***	
	(32.361)		(33.242)		(25.648)	
Inverse Mills Ratio		0.190***		0.103**		0.165***
		(4.293)		(2.358)		(3.171)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.032	0.039	0.030	0.055	0.046	0.064
N	1,161,888	211,632	977,412	209,856	1,161,888	211,632
B. Bottom 25% Underdiversification Sample						
Constant	-0.379***	-0.053	0.087	-0.386	-2.262***	-0.460*
	(-2.873)	(-1.274)	(0.385)	(-1.310)	(-4.787)	(-1.947)

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Table A7 (continued)

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=46-48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Total Financial Assets$_{t-1}$	0.051***	-0.002	0.044***	-0.003**	0.037***	-0.002
	(7.502)	(-1.537)	(7.049)	(-2.020)	(5.933)	(-1.407)
Risk Preference	0.073***	0.007**	0.049**	0.005***	0.063***	0.007*
	(3.654)	(2.098)	(2.527)	(2.588)	(3.419)	(1.959)
Age	0.020*	-0.018***	0.011	-0.017***	0.017	-0.019***
	(1.749)	(-3.162)	(0.965)	(-3.186)	(1.374)	(-3.228)
Gender	-0.111***	-0.022***	-0.118***	-0.021***	-0.124***	-0.023***
	(-6.503)	(-7.809)	(-6.803)	(-8.244)	(-7.712)	(-6.240)
Combined RA Dummy$_{t-1}$	0.530***	0.009	0.495***	0.006	0.479***	0.014
	(35.097)	(0.808)	(27.024)	(0.546)	(26.975)	(1.530)
Baby Assets$_{t-1}$	-0.028***	-0.016***	-0.023***	-0.016***	-0.021***	-0.016***
	(-3.976)	(-6.042)	(-3.473)	(-5.984)	(-3.057)	(-6.800)
Experience of Fund Trading$_{t-1}$			0.428***	-0.255		
			(2.661)	(-1.459)		
Selection Score$_{t-1}$			0.015	0.005		
			(1.546)	(1.558)		
Timing Score$_{t-1}$			0.069***	0.013***		
			(4.460)	(3.929)		
Underdiversification$_{t-1}$					-0.389***	0.051***
					(-15.468)	(5.468)
Limited Attention Bias$_{t-1}$					-0.039***	-0.004**
					(-6.202)	(-2.491)
Disposition Effect Ratio$_{t-1}$					-62.967**	-36.124*
					(-2.186)	(-1.883)
Extrapolation Bias$_{t-1}$					0.011***	-0.004***
					(2.744)	(-2.769)
Gambling Bias$_{t-1}$					-0.020	0.017
					(-0.997)	(0.908)
Anchoring Bias$_{t-1}$					-0.060	0.001
					(-1.248)	(0.564)
Total Turnover$_{t-1}$					-74.177***	3.669***
					(-3.921)	(2.780)
Speculative Turnover$_{t-1}$					-44.073***	-33.042***
					(-2.638)	(-3.331)
Length of Registration$_{t-1}$	0.047***		0.036***		0.042***	
	(10.254)		(8.825)		(8.935)	
Inverse Mills Ratio		0.183***		0.172***		0.199***
		(4.478)		(4.057)		(5.446)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.035	0.024	0.037	0.030	0.047	0.037
N	1,152,288	531,360	1,123,584	530,544	1,105,472	531,360

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel A: Oldest 25% sample (T=48 for Panels 1-2, T=46 for Panel 3 Probit, T=48 for Panel 3 Outcome). Panel B: Youngest 25% sample (T=48 for all panels). Panel 1 includes baseline controls, Panel 2 includes experience, selection, and timing score variables, and Panel 3 includes comprehensive behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A8: Demographics, Skills, and Behavioural Biases for Heterogeneity Analysis by Limited Attention Bias

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
A. Top 25% Limited Attention Sample						
$Constant_{t-1}$	-0.852***	-0.115**	-0.798***	-0.417	-0.904***	-0.111***
	(-6.432)	(-2.076)	(-3.208)	(-1.491)	(-6.457)	(-2.583)
Total Financial $Assets_{t-1}$	0.119***	-0.002	0.094***	-0.006**	0.052***	-0.001
	(6.861)	(-0.434)	(6.941)	(-2.034)	(4.199)	(-0.324)
Risk $Preference_{t-1}$	0.110***	0.019***	0.087***	0.014***	0.092***	0.019***
	(5.110)	(4.022)	(4.853)	(5.508)	(4.923)	(4.862)
Age_{t-1}	0.052***	-0.015**	0.043***	-0.014**	0.054***	-0.016***
	(4.265)	(-2.240)	(3.434)	(-2.244)	(4.539)	(-2.597)
$Gender_{t-1}$	-0.103***	-0.023***	-0.108***	-0.021***	-0.137***	-0.022***
	(-6.983)	(-5.071)	(-6.875)	(-5.162)	(-13.151)	(-4.459)
Combined RA $Dummy_{t-1}$	0.702***	0.017	0.651***	0.008	0.559***	0.017*
	(34.337)	(1.322)	(26.149)	(0.595)	(35.582)	(1.851)
Baby $Assets_{t-1}$	-0.038***	-0.025***	-0.028***	-0.025***	-0.023***	-0.025***
	(-5.371)	(-6.874)	(-3.982)	(-5.914)	(-3.249)	(-7.380)
Exp Fund $Months_{t-1}$			0.066	-0.239		
			(0.484)	(-1.408)		
$Selection_{t-1}$			0.004	0.002		
			(0.502)	(0.692)		
Timing Score $(0\text{-}100)_{t-1}$			-0.001	0.005		
			(-0.064)	(0.983)		
Underdiv $Score_{t-1}$					-0.248***	0.019***
					(-17.213)	(2.979)
Attention $Bias_{t-1}$					-0.037***	0.019***
					(-2.760)	(5.313)
DE $Ratio_{t-1}$					-1.105	-0.118
					(-1.532)	(-0.407)
Extrapolation $Bias_{t-1}$					0.007**	-0.005***
					(2.187)	(-3.959)
Gambling $Bias_{t-1}$					0.002	-0.003*
					(1.360)	(-1.773)
Anchoring $Bias_{t-1}$					-0.025	0.006***
					(-0.859)	(3.140)
Total $Turnover_{t-1}$					-10.250*	0.523
					(-1.963)	(1.379)
Speculative $Turnover_{t-1}$					-11.053***	-1.989*
					(-3.036)	(-1.670)
Length of $Registration_{t-1}$	0.062***		0.052***		0.063***	
	(18.135)		(16.034)		(17.983)	
Inverse Mills Ratio		0.238***		0.221***		0.234***
		(6.673)		(6.354)		(7.257)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.047	0.033	0.042	0.039	0.080	0.067
N	1,368,336	427,584	1,259,520	425,472	1,368,336	427,584
B. Bottom 25% Limited Attention Sample						
$Constant_{t-1}$	-0.795***	-0.172*	-0.698***	-0.278	-0.985*	-0.893***
	(-7.013)	(-1.922)	(-3.194)	(-1.436)	(-1.958)	(-2.863)

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Table A8 (continued)

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=48)	
Variable	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})	Probit (RA_{it})	Outcome (RA_{share})
Total Financial Assets$_{t-1}$	0.159***	0.005	0.130***	0.003	0.079***	0.010*
	(8.328)	(0.720)	(8.265)	(0.452)	(5.825)	(1.692)
Risk Preference$_{t-1}$	0.102***	0.028***	0.086***	0.026***	0.089***	0.032***
	(7.674)	(4.098)	(6.823)	(4.379)	(7.200)	(4.861)
Age$_{t-1}$	0.044***	-0.025***	0.036***	-0.024***	0.046***	-0.023***
	(3.268)	(-3.379)	(2.737)	(-3.404)	(3.488)	(-3.038)
Gender$_{t-1}$	-0.103***	-0.033***	-0.107***	-0.032***	-0.138***	-0.037***
	(-11.172)	(-4.977)	(-11.854)	(-5.419)	(-26.776)	(-5.111)
Combined RA Dummy$_{t-1}$	0.694***	0.017	0.652***	0.010	0.549***	0.047***
	(27.027)	(1.368)	(24.874)	(0.815)	(33.258)	(4.799)
Baby Assets$_{t-1}$	-0.055***	-0.034***	-0.044***	-0.034***	-0.036***	-0.037***
	(-10.920)	(-4.086)	(-9.896)	(-4.049)	(-6.932)	(-4.455)
Exp Fund Months$_{t-1}$			0.121	-0.109		
			(0.996)	(-1.388)		
Selection$_{t-1}$			0.009**	0.004***		
			(2.117)	(2.824)		
Timing Score (0-100)$_{t-1}$			0.003	0.016**		
			(0.462)	(2.138)		
Underdiv Score$_{t-1}$					-0.247***	0.007
					(-16.785)	(1.318)
Attention Bias$_{t-1}$					-0.070	-0.858*
					(-0.101)	(-1.961)
DE Ratio$_{t-1}$					-0.089	-0.125**
					(-1.298)	(-2.127)
Extrapolation Bias$_{t-1}$					-0.025***	-0.012**
					(-2.948)	(-2.281)
Gambling Bias$_{t-1}$					-0.015*	0.020
					(-1.917)	(1.073)
Anchoring Bias$_{t-1}$					-0.012	-0.002
					(-0.430)	(-0.310)
Total Turnover$_{t-1}$					-23.599***	1.839***
					(-2.863)	(3.309)
Speculative Turnover$_{t-1}$					-16.636**	-5.715**
					(-2.178)	(-2.101)
Length of Registration$_{t-1}$	0.061***		0.051***		0.061***	
	(19.903)		(16.370)		(17.426)	
Inverse Mills Ratio		0.262***		0.253***		0.337***
		(5.267)		(5.174)		(7.225)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.044	0.035	0.041	0.041	0.076	0.066
N	1,560,672	459,792	1,420,944	457,632	1,560,672	459,792

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel A: Oldest 25% sample (T=48 for Panels 1-2, T=46 for Panel 3 Probit, T=48 for Panel 3 Outcome). Panel B: Youngest 25% sample (T=48 for all panels). Panel 1 includes baseline controls, Panel 2 includes experience, selection, and timing score variables, and Panel 3 includes comprehensive behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A9: Summary of Heterogeneity Patterns

Dimension	Adoption Rate	Delegation Rate	Key Finding
Age	Old > Young	Young > Old	opposite signs for experience and underdiversification operate among older investors only
Wealth	Rich > Poor	Poor > Rich	opposite signs operate among the wealthy only; negative selection among the wealthy
Timing Skill	Similar	High > Low	opposite signs operate among skilled only; large selection among unskilled
Underdiversification	Diversified > Concentrated	Concentrated > Diversified	Within-group effect 3× larger among concentrated investors
Limited Attention	Similar	Similar	opposite sign operates among inattentive investors only

Notes. "opposite signs" refers to the pattern in which a variable reduces adoption but increases delegation, or vice versa.

A1.6. Robustness Checks: Unweighted Results

We also report results from all main regressions estimated without calibration weights, using the raw stratified sample. The differences between these estimates and our main weighted results are modest throughout.

Table A10: Heckman Two-Stage Regression Baseline Results: Demographics

Variable	Probit (1st Stage)	Outcome (2nd Stage)
Constant	-0.787***	-0.139**
	(-6.745)	(-2.318)
Total Financial Assets$_{t-1}$	0.113***	-0.002
	(8.289)	(-1.192)
Risk Preference	0.109***	0.020***
	(6.289)	(3.875)
Age	0.049***	-0.020***
	(4.036)	(-3.127)
Gender	-0.102***	-0.026***
	(-9.097)	(-5.760)
Combined RA Dummy$_{t-1}$	0.719***	0.029***
	(32.763)	(2.713)
Baby Assets$_{t-1}$	-0.043***	-0.023***
	(-14.045)	(-7.205)
Length of Registration$_{t-1}$	0.062***	
	(24.867)	
Inverse Mills Ratio		0.242***
		(6.849)
Province Control	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.048	0.030
N	4,794,720	1,564,128

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from a Heckman two-stage (Tobit-2) selection model estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. T=48.

Table A11: Heckman Two-Stage Regression Results: Demographics and Investment Skills

Variable	Probit (1st Stage)	Outcome (2nd Stage)
Constant	-0.485***	-0.427
	(-2.966)	(-1.346)
Total Financial Assets$_{t-1}$	0.092***	-0.005**
	(8.542)	(-2.547)
Risk Preference	0.082***	0.017***
	(4.905)	(4.686)
Age	0.036***	-0.020***
	(3.105)	(-3.385)
Gender	-0.105***	-0.021***
	(-9.815)	(-5.619)
Combined RA Dummy$_{t-1}$	0.662***	0.004
	(30.714)	(0.361)
Baby Assets$_{t-1}$	-0.035***	-0.023***
	(-9.407)	(-6.876)
Experience of Fund Trading$_{t-1}$	0.385***	-0.326*
	(3.605)	(-1.872)
Selection Score$_{t-1}$	0.012**	0.002
	(2.203)	(1.082)
Timing Score$_{t-1}$	0.002	0.009**
	(0.323)	(2.317)
Length of Registration$_{t-1}$	0.048***	
	(22.216)	
Inverse Mills Ratio		0.183***
		(4.896)
Province Control	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.046	0.045
N (mean)	4,479,936	1,560,048

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from a Heckman two-stage (Tobit-2) selection model estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. T=48.

Table A12: Heckman Two-Stage Regression Results: Demographics and Behavioural Biases

Variable	Probit	Outcome
Constant	-0.846***	-0.124*
	(-5.901)	(-1.935)
Total Financial Assets$_{t-1}$	0.056***	-0.001
	(7.376)	(-0.385)
Risk Preference	0.095***	0.020***
	(6.145)	(3.859)
Age	0.048***	-0.023***
	(3.773)	(-3.929)
Gender	-0.133***	-0.023***
	(-18.129)	(-4.249)
Combined RA Dummy$_{t-1}$	0.586***	0.027***
	(30.357)	(3.786)
Baby Assets$_{t-1}$	-0.031***	-0.024***
	(-5.781)	(-7.174)
Underdiversification$_{t-1}$	-0.256***	0.027***
	(-21.567)	(7.398)
Limited Attention Bias$_{t-1}$	-0.048***	-0.005***
	(-7.803)	(-3.193)
Disposition Effect Ratio$_{t-1}$	-0.061	0.002
	(-1.218)	(0.122)
Extrapolation Bias$_{t-1}$	0.003	-0.005***
	(0.925)	(-4.258)
Gambling Bias$_{t-1}$	-0.005*	-0.001
	(-1.830)	(-1.115)
Anchoring Bias$_{t-1}$	-0.008	0.001
	(-0.227)	(0.375)
Total Turnover$_{t-1}$	-1.238*	0.304
	(-1.792)	(1.384)
Speculative Turnover$_{t-1}$	-14.982***	-3.602***
	(-3.631)	(-3.022)
Length of Registration$_{t-1}$	0.065***	
	(20.198)	
Inverse Mills Ratio		0.241***
		(6.706)
Province Control	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.079	0.065
N (mean)	4,594,756	1,564,128

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from a Heckman two-stage (Tobit-2) selection model estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. T=48.

Table A13: Heckman Two-Stage Regression Results: Demographics and Fund Returns

	Panel 1 (T=47)		Panel 2 (T=45)		Panel 3 (T=42)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant	-0.687***	-0.102	-0.639***	-0.048	-0.585***	-0.028
	(-6.791)	(-1.452)	(-7.549)	(-1.166)	(-7.887)	(-0.932)
Total Financial Assets$_{t-1}$	0.089***	-0.003	0.087***	-0.005***	0.085***	-0.006***
	(10.124)	(-1.240)	(9.749)	(-2.831)	(9.232)	(-4.380)
Risk Preference	0.099***	0.019***	0.093***	0.015***	0.087***	0.012***
	(7.073)	(3.304)	(7.442)	(4.638)	(8.065)	(5.940)
Age$_{t-1}$	0.044***	-0.021***	0.050***	-0.017***	0.057***	-0.014***
	(3.957)	(-3.356)	(5.920)	(-3.953)	(9.910)	(-4.211)
Gender	-0.109***	-0.026***	-0.105***	-0.022***	-0.102***	-0.020***
	(-11.279)	(-4.885)	(-11.920)	(-7.114)	(-12.064)	(-9.228)
Combined RA Dummy$_{t-1}$	0.690***	0.018	0.701***	0.012	0.712***	0.010
	(34.265)	(1.511)	(51.102)	(1.109)	(78.510)	(1.060)
Baby Assets$_{t-1}$	-0.035***	-0.022***	-0.035***	-0.021***	-0.036***	-0.020***
	(-7.407)	(-6.870)	(-7.319)	(-6.899)	(-6.943)	(-6.804)
Fund Portfolio Return$_{t-1}$	0.002	0.000				
	(0.276)	(0.046)				
Fund Portfolio Return 3M			0.005	0.003		
			(0.504)	(0.515)		
Fund Portfolio Return 6M					0.006	0.005
					(0.599)	(1.192)
Length of Registration$_{t-1}$	0.057***		0.057***		0.059***	
	(20.270)		(20.975)		(20.447)	
Inverse Mills Ratio		0.220***		0.193***		0.179***
		(5.129)		(6.065)		(6.880)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.041	0.030	0.040	0.029	0.039	0.025
N	4,310,558	1,525,573	4,155,345	1,503,720	3,895,626	1,439,466

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged fund portfolio return, Panel 2 includes three-month cumulative return, and Panel 3 includes six-month cumulative return. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A14: Heckman Two-Stage Regression Results: Demographics and RA Returns

	Panel 1 (T=48)		Panel 2 (T=46)		Panel 3 (T=43)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant	-0.787***	-0.151**	-0.731***	-0.131**	-0.669***	-0.080**
	(-6.745)	(-2.547)	(-7.663)	(-2.518)	(-8.760)	(-2.449)
Total Financial Assets$_{t-1}$	0.113***	-0.003**	0.112***	-0.003	0.110***	-0.004***
	(8.289)	(-1.232)	(7.933)	(-1.511)	(7.375)	(-3.060)
Risk Preference	0.109***	0.020***	0.103***	0.018***	0.094***	0.014***
	(6.289)	(3.764)	(6.497)	(4.020)	(6.876)	(5.832)
Age	0.049***	-0.020***	0.055***	-0.017***	0.062***	-0.013***
	(4.036)	(-3.047)	(5.550)	(-3.132)	(9.198)	(-3.350)
Gender	-0.102***	-0.026***	-0.097***	-0.024***	-0.092***	-0.021***
	(-9.097)	(-5.815)	(-9.810)	(-6.417)	(-10.172)	(-9.279)
Combined RA Dummy$_{t-1}$	0.719***	0.032***	0.729***	0.033***	0.744***	0.026**
	(32.763)	(3.216)	(42.035)	(3.113)	(63.464)	(2.455)
Baby Assets$_{t-1}$	-0.043***	-0.024***	-0.044***	-0.023***	-0.044***	-0.021***
	(-14.045)	(-7.251)	(-14.003)	(-7.162)	(-13.185)	(-7.310)
Individual RA Portfolio Return$_{t-1}$		-0.006*				
		(-1.959)				
Individual RA Portfolio Return 3M				-0.003		
				(-1.362)		
Individual RA Portfolio Return 6M						-0.001
						(-0.639)
Length of Registration$_{t-1}$	0.062***		0.062***		0.062***	
	(24.867)		(23.486)		(22.542)	
Inverse Mills Ratio		0.249***		0.242***		0.215***
		(7.280)		(7.343)		(7.815)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.048	0.032	0.046	0.030	0.044	0.027
N	4,794,720	1,564,128	4,596,182	1,545,048	4,297,678	1,492,788

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged individual RA portfolio return, Panel 2 includes three-month cumulative return, and Panel 3 includes six-month cumulative return. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A15: Heckman Two-Stage Regression Results: Demographics Fund Returns, and RA Returns

	Panel 1 (T=48)		Panel 2 (T=46)		Panel 3 (T=43)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant	-0.713***	-0.125***	-0.662***	-0.088**	-0.599***	-0.039
	(-6.429)	(-1.694)	(-7.188)	(-1.558)	(-7.819)	(-1.222)
Total Financial Assets$_{t-1}$	0.089***	-0.003	0.088***	-0.004*	0.086***	-0.006***
	(10.307)	(-1.170)	(9.926)	(-1.848)	(9.460)	(-3.907)
Risk Preference	0.101***	0.019***	0.096***	0.016***	0.089***	0.012***
	(6.913)	(3.119)	(7.260)	(3.552)	(7.866)	(5.435)
Age	0.041***	-0.022***	0.047***	-0.019***	0.055***	-0.015***
	(3.330)	(-3.216)	(4.817)	(-3.502)	(8.420)	(-4.161)
Gender	-0.111***	-0.027***	-0.107***	-0.024***	-0.103***	-0.020***
	(-10.901)	(-4.777)	(-11.642)	(-5.573)	(-12.124)	(-8.921)
Combined RA Dummy$_{t-1}$	0.684***	0.021*	0.696***	0.018*	0.711***	0.013
	(29.995)	(1.905)	(41.160)	(1.706)	(78.673)	(1.326)
Baby Assets$_{t-1}$	-0.034***	-0.022***	-0.035***	-0.022***	-0.036***	-0.020***
	(-7.384)	(-6.996)	(-7.471)	(-6.863)	(-7.120)	(-6.915)
Fund Portfolio Return$_{t-1}$		0.002				
		(0.563)				
Fund Portfolio Return 3M				0.003		
				(0.544)		
Fund Portfolio Return 6M						0.004
						(0.953)
Individual RA Portfolio Return$_{t-1}$		-0.007**				
		(-2.426)				
Individual RA Portfolio Return 3M				-0.004*		
				(-1.681)		
Individual RA Portfolio Return 6M						-0.002
						(-1.004)
Length of Registration$_{t-1}$	0.057***		0.057***		0.059***	
	(20.421)		(19.885)		(20.947)	
Inverse Mills Ratio		0.233***		0.215***		0.186***
		(5.384)		(5.798)		(7.036)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.042	0.033	0.041	0.031	0.040	0.027
N	4,385,376	1,534,128	4,233,978	1,515,792	3,986,767	1,464,795

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged returns, Panel 2 includes three-month cumulative returns, and Panel 3 includes six-month cumulative returns for both fund and individual RA portfolios. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A16: Heckman Two-Stage Regression Results: Demographics and Market RRG

	Panel 1 (T=48)		Panel 2 (T=46)		Panel 3 (T=43)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant	-0.689***	-0.133*	-0.662***	-0.112*	-0.624***	-0.061
	(-5.398)	(-1.760)	(-7.226)	(-1.777)	(-9.048)	(-1.529)
Total Financial Assets$_{t-1}$	0.089***	-0.003	0.088***	-0.004*	0.086***	-0.006***
	(10.318)	(-1.144)	(9.943)	(-1.796)	(9.494)	(-4.068)
Risk Preference	0.101***	0.020***	0.096***	0.017***	0.089***	0.012***
	(6.914)	(3.227)	(7.277)	(3.717)	(7.881)	(5.773)
Age	0.041***	-0.022***	0.047***	-0.019***	0.055***	-0.015***
	(3.337)	(-3.299)	(4.802)	(-3.626)	(8.397)	(-4.215)
Gender	-0.111***	-0.026***	-0.107***	-0.024***	-0.103***	-0.020***
	(-10.911)	(-4.771)	(-11.683)	(-5.566)	(-12.196)	(-9.035)
Combined RA Dummy$_{t-1}$	0.684***	0.018	0.696***	0.014	0.711***	0.010
	(29.961)	(1.529)	(41.180)	(1.268)	(79.399)	(1.042)
Baby Assets$_{t-1}$	-0.034***	-0.022***	-0.035***	-0.022***	-0.036***	-0.020***
	(-7.381)	(-6.977)	(-7.462)	(-6.818)	(-7.092)	(-6.909)
Market RRG$_{t-1}$	0.040	-0.006				
	(0.974)	(-0.298)				
Market RRG 3M			0.044	-0.001		
			(1.319)	(-0.028)		
Market RRG 6M					0.051	0.007
					(1.458)	(0.384)
Length of Registration$_{t-1}$	0.057***		0.057***		0.059***	
	(20.588)		(19.910)		(21.247)	
Inverse Mills Ratio		0.224***		0.205***		0.179***
		(5.169)		(5.511)		(6.949)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.042	0.031	0.041	0.030	0.040	0.026
N	4,385,376	1,534,128	4,233,932	1,515,792	3,984,681	1,464,752

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged market return (Market RRG), Panel 2 includes three-month cumulative market return, and Panel 3 includes six-month cumulative market return. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A17: Heckman Two-Stage Regression Results: Demographics and Asymmetric of Market RRG

	Panel 1 (T=47)		Panel 2 (T=45)		Panel 3 (T=42)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant	-0.894***	-0.132*	-0.975***	-0.099*	-1.056***	-0.061
	(-6.736)	(-1.792)	(-4.822)	(-1.664)	(-4.348)	(-1.565)
Total Financial Assets$_{t-1}$	0.089***	-0.003	0.088***	-0.004*	0.086***	-0.006***
	(10.297)	(-1.138)	(9.833)	(-1.757)	(9.477)	(-3.950)
Risk Preference	0.101***	0.020***	0.095***	0.017***	0.088***	0.012***
	(6.710)	(3.160)	(7.121)	(3.628)	(7.577)	(5.737)
Age	0.041***	-0.022***	0.047***	-0.019***	0.055***	-0.015***
	(3.255)	(-3.244)	(4.723)	(-3.528)	(8.258)	(-4.099)
Gender	-0.111***	-0.027***	-0.107***	-0.024***	-0.103***	-0.020***
	(-10.813)	(-4.692)	(-11.469)	(-5.447)	(-12.056)	(-8.928)
Combined RA Dummy$_{t-1}$	0.683***	0.016	0.696***	0.014	0.710***	0.011
	(29.512)	(1.424)	(40.452)	(1.211)	(78.377)	(1.112)
Baby Assets$_{t-1}$	-0.034***	-0.022***	-0.035***	-0.021***	-0.035***	-0.020***
	(-7.141)	(-6.832)	(-7.288)	(-6.702)	(-6.845)	(-6.743)
Market RRG (Positive)$_{t-1}$	-0.919**	0.004				
	(-2.497)	(0.153)				
Market RRG (Negative)$_{t-1}$	0.085*	-0.005				
	(1.734)	(-0.246)				
Market RRG 3M (Positive)			-1.134*	0.001		
			(-1.726)	(0.036)		
Market RRG 3M (Negative)			0.078**	-0.007		
			(1.994)	(-0.414)		
Market RRG 6M (Positive)					-2.466	-0.012
					(-1.561)	(-1.248)
Market RRG 6M (Negative)					0.094*	0.003
					(1.800)	(0.184)
Length of Registration$_{t-1}$	0.056***		0.057***		0.059***	
	(20.481)		(19.467)		(21.477)	
Inverse Mills Ratio		0.223***		0.204***		0.181***
		(5.027)		(5.378)		(6.982)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.042	0.032	0.041	0.030	0.040	0.026
N	4,289,925	1,502,919	4,138,965	1,484,820	3,887,982	1,433,712

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 separates one-month lagged market return into positive and negative components, Panel 2 uses three-month cumulative returns, and Panel 3 uses six-month cumulative returns. Market RRG (Positive) captures positive market returns, while Market RRG (Negative) captures negative market returns. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A18: Heckman Two-Stage Regression Results: Demographics and Individual RRG

	Panel 1 (T=48)		Panel 2 (T=46)		Panel 3 (T=43)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant	-0.787***	-0.105**	-0.731***	-0.084*	-0.669***	-0.055*
	(-6.745)	(-1.997)	(-7.663)	(-1.877)	(-8.760)	(-1.732)
Total Financial Assets$_{t-1}$	0.113***	-0.003	0.112***	-0.003*	0.110***	-0.004***
	(8.289)	(-1.304)	(7.933)	(-1.740)	(7.375)	(-3.093)
Risk Preference	0.109***	0.018***	0.103***	0.016***	0.094***	0.013***
	(6.289)	(3.739)	(6.497)	(4.055)	(6.876)	(5.274)
Age	0.049***	-0.019***	0.055***	-0.017***	0.062***	-0.013***
	(4.036)	(-3.239)	(5.550)	(-3.347)	(9.198)	(-3.476)
Gender$_{t-1}$	-0.102***	-0.023***	-0.097***	-0.021***	-0.092***	-0.018***
	(-9.097)	(-5.637)	(-9.810)	(-6.368)	(-10.172)	(-8.493)
Combined RA Dummy$_{t-1}$	0.719***	0.021**	0.729***	0.021**	0.744***	0.019*
	(32.763)	(2.253)	(42.035)	(2.072)	(63.464)	(1.879)
Baby Assets$_{t-1}$	-0.043***	-0.022***	-0.044***	-0.022***	-0.044***	-0.020***
	(-14.045)	(-7.016)	(-14.003)	(-6.896)	(-13.185)	(-6.884)
Individual RRG$_{t-1}$		-0.007				
		(-1.500)				
Individual RRG 3M				0.001		
				(0.165)		
Individual RRG 6M						0.007***
						(2.906)
Length of Registration$_{t-1}$	0.062***		0.062***		0.062***	
	(24.867)		(23.486)		(22.542)	
Inverse Mills Ratio		0.214***		0.205***		0.189***
		(6.781)		(6.823)		(7.438)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.048	0.032	0.046	0.030	0.044	0.026
N	4,794,720	1,534,128	4,596,182	1,515,424	4,297,678	1,464,150

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes one-month lagged Individual RRG, Panel 2 includes three-month cumulative Individual RRG, and Panel 3 includes six-month cumulative Individual RRG. Individual RRG is the risk-adjusted alpha of the individual investor's RA portfolio relative to the RA market portfolio. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A19: Heckman Two-Stage Regression Results: Demographics and Asymmetric of Individual RRG

	Panel 1 (T=48)		Panel 2 (T=46)		Panel 3 (T=43)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant$_{t-1}$	-0.787***	-0.100*	-0.731***	-0.081*	-0.669***	-0.051
	(-6.745)	(-1.946)	(-7.663)	(-1.813)	(-8.760)	(-1.628)
Total Financial Assets$_{t-1}$	0.113***	-0.003	0.112***	-0.003*	0.110***	-0.004***
	(8.289)	(-1.378)	(7.933)	(-1.743)	(7.375)	(-2.980)
Risk Preference$_{t-1}$	0.109***	0.017***	0.103***	0.015***	0.094***	0.013***
	(6.289)	(3.756)	(6.497)	(4.020)	(6.876)	(5.233)
Age$_{t-1}$	0.049***	-0.019***	0.055***	-0.017***	0.062***	-0.014***
	(4.036)	(-3.255)	(5.550)	(-3.349)	(9.198)	(-3.629)
Gender$_{t-1}$	-0.102***	-0.022***	-0.097***	-0.021***	-0.092***	-0.018***
	(-9.097)	(-5.757)	(-9.810)	(-6.315)	(-10.172)	(-8.480)
Combined RA Dummy$_{t-1}$	0.719***	0.020**	0.729***	0.021**	0.744***	0.019*
	(32.763)	(2.143)	(42.035)	(2.039)	(63.464)	(1.866)
Baby Assets$_{t-1}$	-0.043***	-0.022***	-0.044***	-0.022***	-0.044***	-0.021***
	(-14.045)	(-7.037)	(-14.003)	(-6.889)	(-13.185)	(-7.258)
Individual RRG (Positive)$_{t-1}$		-0.013*				
		(-1.860)				
Individual RRG (Negative)$_{t-1}$		-0.005				
		(-1.385)				
Individual RRG 3M (Positive)				0.004		
				(1.567)		
Individual RRG 3M (Negative)				-0.006*		
				(-1.720)		
Individual RRG 6M (Positive)						0.010***
						(4.545)
Individual RRG 6M (Negative)						-0.009**
						(-1.979)
Length of Registration	0.062***		0.062***		0.062***	
	(24.867)		(23.486)		(22.542)	
Inverse Mills Ratio		0.212***		0.204***		0.189***
		(6.813)		(6.751)		(7.342)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.048	0.032	0.046	0.031	0.044	0.028
N	4,794,720	1,534,128	4,596,182	1,515,424	4,297,678	1,424,848

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 separates one-month lagged individual return into positive and negative components, Panel 2 uses three-month cumulative returns, and Panel 3 uses six-month cumulative returns. Individual RRG (Positive) captures positive individual returns, while Individual RRG (Negative) captures negative individual returns. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).

Table A20: Heckman Two-Stage Regression Results - First Use Only

	Panel 1 (T=44)		Panel 2 (T=44)		Panel 3 (T=37)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant	-2.114***	0.108	-2.134***	-0.711	-2.127***	0.637
	(-58.106)	(0.251)	(-26.110)	(-0.974)	(-38.242)	(0.638)
Total Financial Assets$_{t-1}$	-0.005	-0.050***	-0.018	-0.065***	-0.046*	0.019
	(-0.228)	(-3.660)	(-0.868)	(-2.681)	(-1.801)	(0.317)
Risk Preference	0.056***	0.004	0.056***	0.016	0.047***	0.011**
	(4.301)	(0.866)	(5.207)	(1.484)	(3.632)	(2.031)
Age	0.015**	-0.020***	0.013*	-0.002	0.015*	-0.019**
	(2.127)	(-3.819)	(1.771)	(-0.146)	(1.874)	(-2.053)
Gender	-0.112***	-0.005	-0.114***	-0.015	-0.135***	0.039
	(-9.453)	(-0.260)	(-10.103)	(-0.570)	(-10.937)	(0.788)
Combined RA Dummy$_{t-1}$	0.311***	-0.085*	0.283***	-0.017	0.220***	-0.110
	(15.088)	(-1.686)	(15.552)	(-0.227)	(11.430)	(-1.133)
Baby Assets$_{t-1}$	0.024***	0.003	0.025***	0.008	0.037***	-0.021
	(6.728)	(0.463)	(5.673)	(0.822)	(8.156)	(-0.814)
Experience of Fund Trading$_{t-1}$			-0.055	-0.280**		
			(-1.234)	(-2.088)		
Selection Score$_{t-1}$			0.007	-0.014		
			(1.507)	(-0.732)		
Timing Score$_{t-1}$			-0.085***	-0.010		
			(-4.580)	(-0.373)		
Underdiversification$_{t-1}$					-0.134***	0.075*
					(-7.590)	(1.648)
Attention Bias$_{t-1}$					0.002	0.001
					(0.150)	(0.349)
Disposition Effect Ratio$_{t-1}$					-0.163*	3.414
					(-1.891)	(1.021)
Extrapolation Bias$_{t-1}$					-0.017**	0.007
					(-2.313)	(0.549)
Gambling Bias$_{t-1}$					-0.003	-0.001
					(-0.786)	(-0.308)
Anchoring Bias$_{t-1}$					-0.006	-0.026
					(-0.147)	(-1.200)
Total Turnover$_{t-1}$					-0.204***	10.018***
					(-3.697)	(3.022)
Speculative Turnover$_{t-1}$					-0.060***	-7.087
					(-2.928)	(-1.453)
Length of Registration$_{t-1}$	0.027***		0.026***		0.029***	
	(3.608)		(3.615)		(3.812)	
Inverse Mills Ratio		0.042		0.250		-0.109
		(0.246)		(0.892)		(-0.274)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2	0.021	0.073	0.028	0.081	0.038	0.124
N	2,389,728	62,656	2,099,240	58,564	2,006,251	54,131

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. This analysis focuses on first-time RA users only. Panel 1 includes baseline specification, Panel 2 adds fund experience and timing variables, and Panel 3 adds behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months). The smaller N and T values compared to the full sample reflect filtering out months where users do not meet first-use criteria.

Table A21: Heckman Two-Stage Regression Results: Demographics, Skills, and Behavioural Biases for Re-participation

	Panel 1 (T=47)		Panel 2 (T=47)		Panel 3 (T=47/44)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant$_{t-1}$	-0.622***	-0.047*	-0.838**	-0.363**	-0.831**	-0.011
	(-5.693)	(-1.759)	(-2.549)	(-2.007)	(-2.542)	(-0.426)
Total Financial Assets$_{t-1}$	0.092***	0.001	0.085***	-0.001	0.057***	0.000
	(7.164)	(0.356)	(6.970)	(-0.466)	(6.067)	(0.009)
Risk Preference$_{t-1}$	0.053***	-0.017***	0.069***	-0.012***	0.058***	-0.013***
	(35.611)	(-5.310)	(23.166)	(-5.645)	(40.773)	(-5.091)
Age$_{t-1}$	0.106***	-0.000	0.096***	0.001	0.105***	-0.003
	(23.208)	(-0.180)	(17.274)	(0.242)	(23.032)	(-1.285)
Gender$_{t-1}$	0.131***	0.030***	0.130***	0.041***	0.105***	0.025***
	(18.629)	(5.901)	(18.203)	(6.242)	(10.673)	(5.587)
Combined RA Dummy$_{t-1}$	0.411***	0.000	0.417***	0.027	0.355***	0.016**
	(14.074)	(0.008)	(13.385)	(1.642)	(13.676)	(1.997)
Baby Assets$_{t-1}$	-0.022***	-0.025***	-0.014**	-0.022***	-0.016**	-0.024***
	(-2.813)	(-4.664)	(-2.248)	(-5.522)	(-2.068)	(-5.547)
Experience of Fund Trading$_{t-1}$			0.301**	-0.081		
			(2.008)	(-1.129)		
Selection Score$_{t-1}$			0.008	0.003		
			(0.906)	(1.241)		
Timing Score$_{t-1}$			-0.017	0.015**		
			(-0.545)	(2.398)		
Underdiversification$_{t-1}$					-0.176***	0.028***
					(-10.958)	(5.952)
Attention Bias$_{t-1}$					-0.051***	-0.011***
					(-5.276)	(-3.409)
Disposition Effect Ratio$_{t-1}$					17.460	0.121
					(0.965)	(1.554)
Extrapolation Bias$_{t-1}$					0.011	-0.003
					(1.437)	(-1.196)
Gambling Bias$_{t-1}$					0.018	-0.009
					(0.995)	(-1.611)
Anchoring Bias$_{t-1}$					0.008	0.012**
					(0.349)	(2.193)
Total Turnover$_{t-1}$					-1.725	0.222
					(-1.588)	(1.023)
Speculative Turnover$_{t-1}$					-26.014***	-11.445***
					(-3.626)	(-2.876)
Length of Registration	0.034***		0.024***		0.036***	
	(10.867)		(7.858)		(9.585)	
Inverse Mills Ratio		0.696***		0.546***		0.615***
		(4.690)		(9.386)		(5.669)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2	0.028	0.031	0.030	0.048	0.045	0.065
N	2,214,969	1,432,372	2,214,969	1,432,372	2,042,216	1,432,372

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes baseline specification, Panel 2 adds fund experience and timing variables, and Panel 3 adds behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months). For Panel 3, T=47 for outcome and T=44 for probit.

Table A22: Heckman Two-Stage Regression Results: Rule-based Investment Automation

	Panel 1 (T=48)		Panel 2 (T=48)		Panel 3 (T=28)	
Variable	Probit	Outcome	Probit	Outcome	Probit	Outcome
Constant$_{t-1}$	-0.653***	1.017***	0.543	0.806***	-1.096***	1.018***
	(-16.097)	(19.707)	(0.687)	(6.306)	(-4.515)	(30.237)
Total Financial Assets$_{t-1}$	0.096***	-0.045***	0.065***	-0.044***	0.048***	-0.032***
	(10.907)	(-16.847)	(9.023)	(-16.582)	(9.423)	(-29.707)
Risk Preference$_{t-1}$	0.069***	-0.028***	0.034***	-0.028***	0.051***	-0.021***
	(5.248)	(-6.293)	(4.053)	(-8.867)	(3.971)	(-6.679)
Age$_{t-1}$	0.110***	-0.005	0.094***	-0.008**	0.105***	-0.012***
	(26.475)	(-1.159)	(18.555)	(-2.281)	(16.720)	(-4.846)
Gender$_{t-1}$	0.010	0.025***	0.017	0.023***	-0.011	0.035***
	(0.736)	(7.813)	(1.019)	(6.825)	(-0.498)	(7.225)
Combined RA Dummy$_{t-1}$	0.312***	-0.051***	0.231***	-0.049***	0.198***	-0.011
	(41.834)	(-3.340)	(15.269)	(-3.503)	(13.261)	(-1.063)
Baby Assets$_{t-1}$	-0.048***	0.009***	-0.037***	0.010***	-0.032***	0.009***
	(-10.856)	(6.753)	(-13.108)	(7.812)	(-7.771)	(7.410)
Experience of Fund Trading$_{t-1}$			1.005**	-0.151**		
			(2.173)	(-2.086)		
Selection Score$_{t-1}$			-0.006	-0.001		
			(-0.947)	(-0.342)		
Timing Score$_{t-1}$			-0.115***	0.010		
			(-11.884)	(0.862)		
Underdiversification$_{t-1}$					-0.169***	0.113***
					(-9.487)	(42.033)
Attention Bias$_{t-1}$					-0.092***	-0.005
					(-3.242)	(-1.238)
Disposition Effect Ratio$_{t-1}$					-0.435	0.049
					(-1.486)	(1.098)
Extrapolation Bias$_{t-1}$					0.035*	-0.008**
					(1.794)	(-2.305)
Gambling Bias$_{t-1}$					-0.023***	-0.007***
					(-3.450)	(-3.734)
Anchoring Bias$_{t-1}$					-0.035	0.004
					(-0.586)	(1.393)
Total Turnover$_{t-1}$					-64.678*	-5.382*
					(-1.916)	(-1.945)
Speculative Turnover$_{t-1}$					27.468*	-13.323***
					(1.761)	(-4.154)
Length of Registration	0.110***		0.091***		0.104***	
	(18.387)		(26.848)		(12.989)	
Inverse Mills Ratio		-0.192***		-0.203***		-0.246***
		(-4.312)		(-4.048)		(-9.502)
Province Control	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2 (mean)	0.029	0.027	0.036	0.042	0.068	0.091
N	4,794,720	1,583,088	4,479,936	1,575,168	2,797,984	944,440

Notes. Coefficients with Newey–West (HAC) corrected t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Estimates come from Heckman two-stage (Tobit-2) selection models estimated monthly. Reported coefficients are Fama–MacBeth cross-sectional averages across months. Panel 1 includes baseline specification, Panel 2 adds fund experience and timing variables, and Panel 3 adds behavioral bias measures. All independent variables are lagged by one period. Pseudo R^2 (selection) and R^2 (outcome) are averaged across months. N is calculated as mean N times T (number of months).