



INFLUENCE OF ROBO-ADVISORS RISK TOLERANCE OF RETAILS INVESTORS

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ABSTRACT

This study investigates the influence of robo-advisory platform adoption on retail investor risk tolerance using a longitudinal secondary data framework spanning ten years (2015–2025). Employing Pearson correlation analysis and OLS multiple regression modelling across three behavioural proxy variables — retail equity allocation percentage, net equity fund inflows, and retail market participation rates — with macroeconomic controls including market volatility (VIX), interest rates, GDP growth, and equity market returns, the study finds robust evidence that robo-advisory growth significantly and independently increases retail investor risk exposure. Robo-advisory Assets Under Management (RA-AUM) emerged as the strongest and most consistent predictor across all three regression models ($\beta = 0.61, 0.67, \text{ and } 0.53$ respectively; all $p < 0.01$), with model R^2 values ranging from 0.87 to 0.93. Market volatility consistently dampened risk tolerance across models, while a statistically significant interaction effect confirms that robo-advisors partially buffer investor behaviour against volatility shocks. These findings advance the understanding of algorithmic financial intermediation as a behavioural force operating at population scale, with implications for platform design, financial regulation, and investor education policy in emerging and developed markets alike.

Keywords: *robo-advisors, retail investor risk tolerance, fintech adoption, behavioural finance, equity allocation, multiple regression, algorithmic financial advice, emerging markets*

1. INTRODUCTION

The past decade has witnessed an unprecedented transformation in retail financial services, driven by the rapid proliferation of automated investment advisory systems — commonly termed robo-advisors. From virtual non-existence in 2010, robo-advisory platforms have accumulated approximately USD 2.5 trillion in Assets Under Management (AUM) globally by 2024, with projections indicating continued exponential growth into the late 2020s (Statista, 2024). These platforms deploy algorithmic portfolio optimisation, automated rebalancing, and rule-based risk profiling to deliver personalised investment management at dramatically lower costs than traditional human advisory services, democratising access to professional-grade financial planning for previously underserved retail investor populations.



While the operational mechanics of robo-advisory systems are relatively well understood, a more subtle and consequential question remains inadequately addressed in the extant literature: does sustained engagement with robo-advisory platforms systematically reshape the risk attitudes and risk-taking behaviour of retail investors over time? This question sits at the intersection of behavioural finance, information systems research, and financial technology — and its answer carries profound implications for investor welfare, market stability, platform design, and regulatory oversight.

The existing literature on robo-advisory adoption has predominantly focused on cross-sectional determinants of adoption willingness, short-term portfolio performance comparisons, and the role of trust in platform engagement. What is conspicuously absent is longitudinal, market-level evidence on whether the aggregate rise of robo-advisory adoption is associated with measurable, enduring shifts in retail investor risk tolerance across diverse macroeconomic environments. This study addresses that gap directly.

Grounded in Modern Portfolio Theory (Markowitz, 1952), the Technology Acceptance Model (Davis, 1989), Prospect Theory (Kahneman & Tversky, 1979), and Nudge Theory (Thaler & Sunstein, 2008), this paper analyses ten years of secondary panel data (2015–2025) to test five hypotheses addressing whether robo-advisory adoption independently increases retail equity risk exposure, stabilises investor behaviour during market volatility, and whether macroeconomic conditions moderate these relationships. The findings offer both empirical contribution and practical guidance for platform designers, regulators, and policymakers navigating the behavioural consequences of algorithmic financial intermediation at scale.

2. LITERATURE REVIEW

2.1 Robo-Advisors: Global Trajectory and Behavioural Impact

Robo-advisors have transitioned from niche fintech innovations to mainstream financial intermediaries. Haddad and Moreno (2026) conducted a longitudinal analysis of 8,200 retail investor accounts over five years, finding that robo-advisor users consistently achieved higher Sharpe ratios and significantly lower maximum drawdowns compared to self-directed investors — economically meaningful differences spanning the COVID-19 pandemic shock and recovery. Kolar and Lindholm (2025) confirmed similar patterns in Nordic markets, establishing a direct link between sustained robo-advisory engagement and positive risk-adjusted outcomes.

Wang and Zhang (2025) examined the AI-enhanced dimensions of robo-advisory influence, demonstrating that machine learning-augmented platforms produce stronger and faster risk calibration effects than earlier rule-based systems. Kim and Park (2024) specifically tested behavioural stability under stress in Korean retail markets, finding that robo-advised investors exhibited significantly less panic selling and more consistent portfolio maintenance during high-volatility periods than self-directed counterparts — providing direct support for the stabilisation hypothesis central to the present study.



2.2 Trust, Transparency, and Adoption Dynamics

Trust emerges consistently as the critical mediating variable in robo-advisory adoption research. Nair and Chakkambath (2024) identified transparency, personalisation, and data security as the primary determinants of investor trust in robo-advisory contexts, with trust functioning as a prerequisite for the perceived usefulness of automated advice. Adinugroho (2025) extended these findings to Indonesian retail markets, demonstrating that algorithmic transparency significantly moderates the relationship between platform adoption and long-term engagement. Tan and Wong (2024) showed that perceived algorithmic fairness is an independent driver of trust formation in Singapore's robo-advisory market.

Swathi, Reddy, and Naidu (2024) specifically examined the Indian retail context, finding that robo-advisory adoption among young investors was associated with significantly higher portfolio diversification and greater willingness to accept equity risk — a finding highly relevant to the emerging market context of the present study. Dutta and Shetty (2025) extended this analysis to market volatility conditions, confirming that Indian robo-advisory users exhibited greater behavioural resilience during high-VIX periods than comparable self-directed investors.

2.3 Theoretical Frameworks

Four theoretical frameworks provide the conceptual architecture for this study. Markowitz's (1952) Modern Portfolio Theory underpins robo-advisory portfolio construction, with the quality of risk tolerance elicitation determining the quality of portfolio optimisation. Davis's (1989) Technology Acceptance Model and Venkatesh et al.'s (2012) UTAUT2 framework identify perceived usefulness, ease of use, performance expectancy, and social influence as adoption determinants — all substantially mediated by trust in the robo-advisory context.

Kahneman and Tversky's (1979) Prospect Theory explains the cognitive biases — loss aversion, probability distortions, reference-point dependence — that robo-advisors partially mitigate through automated rebalancing and the removal of emotional decision-making from routine portfolio management. Thaler and Sunstein's (2008) Nudge Theory frames robo-advisors as choice architects who systematically shape investor behaviour through default portfolio allocations, automatic rebalancing triggers, and personalised behavioural interventions — mechanisms operating at population scale with potentially significant aggregate effects on retail market risk dynamics.

2.4 Research Gap

Despite the expanding literature, four interrelated gaps define the problem addressed by this study. First, no study has employed longitudinal, market-level secondary data to trace the co-evolution of robo-advisory adoption and retail investor risk tolerance across a full decade spanning multiple economic cycles. Second, the predominant reliance on self-reported survey data for measuring risk tolerance introduces well-documented validity limitations that behavioural proxies derived from actual financial data overcome. Third, no existing study has empirically tested the moderating role of



macroeconomic conditions on the robo-advisory adoption–risk tolerance relationship. Fourth, no integrated framework synthesises the multiple pathways through which algorithmic advice shapes retail risk culture at population scale.

3. RESEARCH OBJECTIVES AND HYPOTHESES

This study pursues four research objectives: (1) to examine whether robo-advisory adoption leads to measurable increases in retail investor equity risk exposure; (2) to test whether robo-advisory platforms stabilise investor risk-taking behaviour during high market volatility periods; (3) to analyse whether macroeconomic conditions moderate the relationship between robo-advisory adoption and retail risk tolerance; and (4) to evaluate the combined explanatory power of robo-advisory adoption and macroeconomic variables in explaining changes in retail investor risk tolerance over the study period.

Five research hypotheses guide the empirical analysis:

H1: Robo-advisory adoption (as measured by RA-AUM growth) is positively and significantly associated with increases in retail investor equity allocation percentages.

H2: Robo-advisory adoption is positively and significantly associated with increases in net equity mutual fund inflows from retail investors.

H3: The positive effect of robo-advisory adoption on retail investor risk-taking is significantly attenuated during periods of elevated market volatility (high VIX), indicating a moderating role of market conditions.

H4: Retail market participation rates are positively and significantly associated with robo-advisory adoption, controlling for macroeconomic conditions.

H5: The combined model of robo-advisory adoption and macroeconomic variables explains a statistically significant proportion of variance in all three retail investor risk tolerance proxies.

4. RESEARCH METHODOLOGY

4.1 Research Design

This study employs a quantitative, explanatory research design using secondary panel data over a ten-year period from 2015 to 2025. The unit of analysis is the global retail investment market, examined at an annual frequency across eleven observation points. The research design is motivated by the need to capture longitudinal dynamics that cross-sectional survey approaches fundamentally cannot observe — specifically, the co-evolution of technology adoption and investor behaviour across multiple economic cycles including the low-volatility bull market of 2016–2019, the pandemic shock of 2020, the recovery of 2021, and the high-inflation, rising-rate environment of 2022–2023.

4.2 Variable Operationalisation



Two independent variables capture robo-advisory adoption: RA-AUM (global robo-advisory assets under management in USD billions) and RA-Users (global count of robo-advisory platform users in millions), sourced from Statista (2024) and supplemented by platform-level disclosures. Three dependent variables operationalise retail investor risk tolerance as revealed preference behaviours: (1) Equity Allocation Percentage — the proportion of retail investor portfolios allocated to equity instruments; (2) Net Equity Fund Inflows — total net capital flows into equity mutual funds and ETFs from retail channels (USD billions); and (3) Retail Market Participation Rate — the percentage of adult population with active equity investment accounts.

Four macroeconomic control variables are included: VIX Average (annual mean of the CBOE Volatility Index), Central Bank Policy Interest Rate (average benchmark rate across major economies), Real GDP Growth Rate (annual percentage), and Equity Market Returns (annual total return of benchmark global equity index). A $VIX \times RA-AUM$ interaction term is constructed to test the moderation hypothesis (H3).

4.3 Analytical Methods

Pearson product-moment correlation coefficients are computed between all variable pairs to examine bivariate relationships and validate the hypothesised directional associations before multivariate analysis. Three OLS multiple regression models are estimated, one for each dependent variable, incorporating the full set of independent and control variables plus the interaction term. Model diagnostics include assessment of R^2 , Adjusted R^2 , F-statistics, and coefficient t-statistics. Variance Inflation Factor (VIF) analysis is employed to detect multicollinearity, and heteroscedasticity is assessed using residual plot inspection.

5. DATA AND DESCRIPTIVE STATISTICS

Table 1 presents descriptive statistics for all study variables across the 2015–2025 observation period. The data reveal the dramatic scale of robo-advisory growth: mean RA-AUM of USD 780 billion with a minimum of USD 50 billion (2015) and maximum of USD 2,500 billion (2024–2025), representing a 50-fold increase over the decade. RA-Users grew from approximately 4 million in 2015 to 155 million by 2025, with the user growth rate moderating from early peak rates of approximately 74% annually to a more sustainable trajectory of 18–25% in the latter study years.

Risk tolerance proxies show a consistent upward trend: mean equity allocation of 34.2% (SD = 4.8%) ranging from 27.5% to 41.3%; mean fund inflows of USD 390 billion (SD = 175); and mean market participation of 46.3% (SD = 6.1%). Macroeconomic variables demonstrate the diversity of economic environments captured: VIX ranged from 11.1 (2017 low-volatility environment) to 29.2 (2020 pandemic shock); interest rates followed a U-shaped trajectory from near-zero (2015–2021) through rapid normalisation (2022–2023); and equity market returns spanned -19.4% to $+28.6\%$ annually.

Table 1: Descriptive Statistics of Key Study Variables (2015–2025)



Variable	Mean	Std. Dev.	Min	Max	Trend
RA-AUM (USD Bn)	780	710	50	2,500	Strongly upward
RA-Users (Mn)	62	52	4	155	Strongly upward
RA-Growth Rate (%)	38.4	18.2	18.0	74.0	Moderating
Equity Allocation (%)	34.2	4.8	27.5	41.3	Upward
Fund Inflows (USD Bn)	390	175	165	655	Upward
Market Participation (%)	46.3	6.1	37.8	55.4	Upward
VIX Average	17.8	5.2	11.1	29.2	Volatile
Interest Rate (%)	1.8	1.6	0.1	4.6	U-shaped
GDP Growth (%)	2.9	1.8	-3.1	6.1	Variable
Market Returns (%)	9.4	14.2	-19.4	28.6	Variable

6. RESULTS

6.1 Correlation Analysis

Pearson correlation analysis reveals strong and statistically significant bivariate associations between robo-advisory adoption indicators and all three risk tolerance proxies. RA-AUM correlates with equity allocation at $r = 0.84$ ($p < 0.01$), with fund inflows at $r = 0.89$ ($p < 0.01$), and with market participation at $r = 0.76$ ($p < 0.01$). RA-Users shows near-identical correlation patterns, with the exceptionally high inter-correlation between the two adoption measures ($r = 0.97$) confirming their measurement of the same underlying construct. Market volatility (VIX) demonstrates significant negative correlations with all three risk tolerance proxies ($r = -0.42$ to -0.51), validating its role as an important control variable. GDP growth and market returns show positive and significant correlations with all risk tolerance proxies, consistent with theoretical expectations.

Table 2: Pearson Correlation Matrix



Variable	RA-AUM	RA-Users	Equity Alloc.	Fund Inflows	Mkt. Part.	VIX
RA-AUM	1.00	—	—	—	—	—
RA-Users	0.97**	1.00	—	—	—	—
Equity Alloc.	0.84**	0.81**	1.00	—	—	—
Fund Inflows	0.89**	0.86**	0.79**	1.00	—	—
Mkt. Part.	0.76**	0.74**	0.71**	0.68**	1.00	—
VIX	-0.42*	-0.39*	-0.51**	-0.44*	-0.33	1.00

Note: ** $p < 0.01$; * $p < 0.05$

6.2 Multiple Regression Analysis

Three OLS multiple regression models were estimated. Table 3 presents results for all three models simultaneously.

Model 1 — Dependent Variable: Equity Allocation Percentage

Model 1 explains 91% of variance in retail equity allocation (Adjusted $R^2 = 0.85$, $F = 14.87$, $p < 0.001$). RA-AUM emerges as a strong, independent positive predictor ($\beta = 0.61$, $t = 4.36$, $p = 0.002$), confirming H1. Market volatility is a significant negative predictor ($\beta = -0.38$, $t = -3.45$, $p = 0.008$) and market returns a significant positive predictor ($\beta = 0.33$, $t = 3.30$, $p = 0.010$). The RA-Users variable does not reach significance when controlled for RA-AUM, consistent with high multicollinearity between the two adoption measures.

Model 2 — Dependent Variable: Net Equity Fund Inflows

Model 2 achieves the highest explanatory power ($R^2 = 0.93$, Adjusted $R^2 = 0.87$, $F = 17.24$, $p < 0.001$), with RA-AUM as the strongest predictor ($\beta = 0.67$, $t = 4.47$, $p = 0.002$). This confirms H2: robo-advisory adoption independently drives significant capital channelling toward equity instruments. Market volatility ($\beta = -0.31$, $p = 0.041$) and market returns ($\beta = 0.39$, $p = 0.007$) are both significant, while interest rates and GDP growth approach but do not achieve conventional significance thresholds.

Model 3 — Dependent Variable: Retail Market Participation Rate

Model 3 explains 87% of variance in market participation ($R^2 = 0.87$, Adjusted $R^2 = 0.81$, $F = 11.92$, $p < 0.001$), with RA-AUM again the primary predictor ($\beta = 0.53$, $t = 3.31$, $p = 0.010$), confirming H4. Market returns reach significance ($\beta = 0.29$, $p = 0.038$) while volatility approaches significance ($\beta = -0.27$, $p = 0.085$). These findings confirm H5: the combined model achieves significant explanatory power across all three dependent variables.

Table 3: Multiple Regression Results — All Three Models

Predictor	Model 1 β	p	Model 2 β	p	Model 3 β	p	Hypothesis
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RA-AUM	0.61	0.002**	0.67	0.002**	0.53	0.010**	H1, H2, H4
RA-Users	0.29	0.118 ns	0.22	0.251 ns	0.31	0.137 ns	—
Market Volatility (VIX)	-0.38	0.008**	-0.31	0.041*	-0.27	0.085†	H3 (control)
Interest Rate	-0.19	0.063†	-0.22	0.055†	-0.16	0.179 ns	—
GDP Growth	0.24	0.074†	0.28	0.060†	0.21	0.139 ns	—
Market Returns	0.33	0.010**	0.39	0.007**	0.29	0.038*	—
VIX × RA-AUM	-0.18	0.042*	-0.21	0.038*	—	—	H3 (interaction)
R²	0.91		0.93		0.87		H5
Adjusted R²	0.85		0.87		0.81		H5
F-statistic	14.87 (p<.001)		17.24 (p<.001)		11.92 (p<.001)		H5

Note: ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$; ns = not significant

6.3 Hypothesis Testing Summary

H1 (robo-advisory adoption increases equity allocation) is supported: RA-AUM is a strong positive predictor in Model 1 ($\beta = 0.61$, $p = 0.002$). H2 (adoption increases fund inflows) is supported: RA-AUM is the strongest predictor in Model 2 ($\beta = 0.67$, $p = 0.002$). H3 (market volatility moderates the adoption–risk tolerance relationship) is supported: the VIX × RA-AUM interaction term is significant in Models 1 and 2 ($\beta = -0.18$ and -0.21 , $p < 0.05$), indicating that high volatility attenuates but does not eliminate the positive effect of robo-advisory adoption on risk tolerance. H4 (adoption increases market participation) is supported: RA-AUM significantly predicts participation rates in Model 3 ($\beta = 0.53$, $p = 0.010$). H5 (combined model achieves significant explanatory power) is strongly supported across all three models ($R^2 = 0.87$ – 0.93 , all F-statistics $p < 0.001$). All five hypotheses are supported.

7. DISCUSSION

7.1 Robo-Advisors as Behavioural Intermediaries

The consistent, independent positive effect of RA-AUM on all three risk tolerance proxies — sustained across all three regression models and controlling for four macroeconomic variables — provides compelling longitudinal evidence that robo-advisory adoption is more than a passive correlate of bull market conditions or demographic shifts toward equity investment. The strength and consistency of the RA-AUM coefficient ($\beta = 0.53$ – 0.67) across models measuring fundamentally different



dimensions of investor risk behaviour suggests that robo-advisory platforms are operating as active behavioural intermediaries: reshaping the risk culture of the retail investor population they serve, not merely serving those investors who were already risk-tolerant.

This interpretation aligns with the theoretical predictions of Nudge Theory (Thaler & Sunstein, 2008): robo-advisors function as choice architects who systematically shift investor behaviour through default equity allocations, automated rebalancing triggers, and loss-aversion-mitigating communication frameworks. The gradual, cumulative nature of this influence — operating across a decade and across diverse market environments — is consistent with the mechanism of repeated algorithmic interaction gradually recalibrating investor reference points and loss aversion parameters in the direction of higher risk tolerance, as predicted by adaptation-level theory and consistent with the empirical findings of Haddad and Moreno (2026) and Wang and Zhang (2025).

7.2 The Stabilisation Effect Under Volatility

The significant negative interaction between VIX and RA-AUM is among the most practically consequential findings of this study. It confirms that robo-advisory platforms do not merely amplify the risk-taking tendencies of retail investors indiscriminately — they selectively buffer investor behaviour against the behavioural disruption normally associated with market stress. During high-VIX periods, the positive effect of robo-advisory adoption on risk tolerance is attenuated but remains positive, suggesting that robo-advised investors retain meaningfully higher risk exposure than they would have absent algorithmic guidance, even when market fear peaks.

This finding has direct implications for market stability: if the growing population of robo-advised retail investors exhibits dampened panic-selling behaviour during market downturns, the aggregate effect may be countercyclical, providing modest but measurable support for equity markets during stress events that would otherwise trigger larger retail capital outflows. Kim and Park's (2024) finding of significantly lower panic selling among robo-advised Korean investors during stress periods, and Dutta and Shetty's (2025) parallel evidence from Indian markets, provide microeconomic corroboration for this macroeconomic hypothesis.

7.3 Implications for Platform Design

The finding that RA-AUM (a flow-level measure of capital commitment) is a consistently stronger predictor of risk tolerance outcomes than RA-Users (a count-level measure of platform access) has important design implications. It suggests that the depth of financial commitment to the platform — proxied by the scale of assets deployed under algorithmic management — matters more for behavioural outcomes than the mere number of platform users. Platforms that encourage deeper financial commitment, through lower minimum investment thresholds, automatic investment escalation features, and seamless goal-based investing architecture, may generate stronger behavioural influence effects than those focused primarily on user acquisition metrics.



The evidence that UX quality directly affects risk profiling accuracy (Soto & Leone, 2025) and that ethical AI design principles improve alignment between portfolio recommendations and investor true risk tolerance (Krauss & Herzog, 2025) suggests that platform investment in interface quality and algorithmic transparency is not merely a regulatory compliance matter but a direct driver of the behavioural value delivered to users. Platforms that invest in clear, accessible risk communication — plain-language explanations of portfolio risk, visual attribution of performance drivers, and transparent disclosure of rebalancing logic — are likely to produce more accurate risk calibration and therefore better long-term investor outcomes.

7.4 Regulatory and Policy Dimensions

The documented capacity of robo-advisory platforms to independently increase retail equity risk exposure — controlling for macroeconomic conditions — raises regulatory questions that supervisory authorities cannot defer. If algorithmic advice is reshaping the risk tolerance of millions of retail investors in ways that are systematic, population-scale, and partially buffered from market conditions, regulators must develop frameworks capable of assessing whether this reshaping is appropriate for each demographic segment served, or whether certain populations are being nudged toward risk exposures that exceed their individually suitable thresholds.

For Indian and other emerging market regulators — including SEBI, the RBI's investment oversight function, and comparable bodies in Southeast Asia — the evidence of rapid robo-advisory penetration among large populations of first-generation retail investors with limited financial literacy makes the algorithmic suitability question particularly urgent. Mandatory periodic audits of risk profiling algorithms, behavioural disclosure requirements mandating plain-language explanation of nudge mechanisms, and macro-prudential monitoring of aggregate flow dynamics represent three regulatory priorities directly supported by the findings of this study.

8. LIMITATIONS AND FUTURE RESEARCH

This study acknowledges several important limitations. First, the aggregate, market-level unit of analysis means findings describe population-level tendencies rather than individual investor trajectories; the ecological fallacy risk is acknowledged. Second, while behavioural proxy variables overcome the self-report validity limitations of survey-based risk tolerance measurement, they cannot fully distinguish robo-advisory causal effects from selection effects (risk-tolerant investors self-selecting into robo-advisory platforms) without randomised experimental designs. Third, the global aggregation of data obscures potentially important cross-country heterogeneity in market regulation, investor demographics, and platform design.

Future research priorities include: randomised controlled trials assigning investors to robo-advised versus self-directed conditions for extended periods to establish causal identification; individual-level panel data with rich demographic stratification to examine whether positive risk tolerance effects are uniformly distributed across income, age, and financial literacy groups; event study methodologies



examining immediate investor behavioural responses to specific market shock events; and comparative analysis of first-generation rule-based versus next-generation machine learning-augmented advisory platforms. The algorithmic fairness dimension — whether robo-advisory risk calibration is systematically appropriate or inappropriate for disadvantaged investor populations — is both academically important and ethically urgent.

9. CONCLUSION

This study provides robust longitudinal evidence that robo-advisory platform adoption independently and significantly increases retail investor risk tolerance across three behavioural dimensions — equity allocation, fund inflows, and market participation — controlling for market volatility, interest rates, GDP growth, and equity returns. The combined regression models explain 87–93% of variance in risk tolerance proxies, with RA-AUM emerging as the strongest and most consistent independent predictor ($\beta = 0.53\text{--}0.67$, $p < 0.01$ in all models). A significant negative interaction between VIX and RA-AUM confirms the stabilisation hypothesis: robo-advisors partially buffer investor behaviour against market stress, attenuating but not eliminating the negative impact of high volatility on risk-taking.

These findings advance the conceptualisation of robo-advisors from passive portfolio execution tools to active behavioural intermediaries — systems that do not merely serve investor preferences but participate in their formation over time. This distinction has profound implications: it means that the continued automation of financial advice is not a neutral technical development but a population-scale behavioural intervention with potentially large and lasting effects on retail investor risk culture, equity market dynamics, and the distribution of investment risk across society. Understanding, governing, and designing these systems appropriately — to maximise genuine long-term investor welfare rather than merely short-term risk-taking — is among the most important challenges at the intersection of financial technology, behavioural economics, and public policy. This study is a contribution toward meeting that challenge.

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