The Financial Literacy Divide: Cognitive Decline, Fintech Adoption, and Elder Fraud Risk

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Abstract

This paper investigates how financial literacy mediates the impact of cognitive decline on fintech adoption and fraud risk among older U.S. adults. Using a framework combining bounded rationality and rational crime theory, we propose a "perception discount factor" (PDF) to model the interplay of literacy and cognitive decline. Analyzing Health and Retirement Study data (2002–2022), we first assess cognitive decline's effect on financial literacy through nonlinear mixed-effects panel regression. We then examine the financial literacy divide's influence on fintech adoption and fraud risk, employing Heckman selection models to correct for biases toward high-functioning respondents. Findings reveal that high-literacy elders show non-monotonic fintech adoption, with increased engagement heightening fraud exposure, while low-literacy elders remain consistently disengaged. Cognitive impairment heightens risk, but fraud disproportionately targets educated, affluent elders due to overconfidence, challenging traditional vulnerability assumptions.

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1 Introduction

The convergence of Financial Technology (Fintech) with an aging population creates a pressing societal and economic challenge. While fintech enhances financial inclusion for elders—through tools like mobile banking and digital payments—it also heightens exploitation risks[1]. Rapid post-COVID-19 adoption exacerbates vulnerabilities tied to low financial literacy and cognitive decline, leading to economic losses and debates on whether fintech amplifies macroeconomic inequalities, prompting calls for regulatory safeguards against fraud.

In a digitized economy, older adults lacking wealth management skills are prone to fintech and cyber fraud (Egan et al., 2019, Kim et al., 2021). A growing body of economic research examines the role of financial literacy in aging (Agarwal et al., 2009, Finke et al., 2017, Korniotis and Kumar, 2011, Mazzonna and Peracchi, 2024), sparking discussions on its protective effects and policy responses, such as targeted education.

For elders at risk of cognitive decline, retained financial literacy, defined as the portion of an individual's objective financial knowledge and skills that persists or is maintained despite age-related cognitive decline, serves as a "reserve battery" to power financial decision making. Yet, it is unclear whether high literacy always results in more prudent decisions. When adopting new fintech tools, cognitive limits often lead elders to "satisfice" (seek satisfactory rather than optimal outcomes) using heuristics and simplified mental models rather than fully rational optimization (Simon, 1957). For example, those with low levels of retained financial literacy may find a new AI-powered tool too complex to grasp. On the contrary, more literate elders may be overconfident about their ability to navigate the new product, exposing them to unguarded threats.

Using Health and Retirement Study (HRS) data, this paper tests financial literacy's "dual role" in U.S. older adults, serving as both a protective shield against financial exploitation and a potential catalyst for overconfidence-driven fraud. We employ fraud and fintech-related outcomes from the Leaving-Behind Questionaries (LBQ), which is self-administered and mailed back by voluntary respondents who completed the Core HRS survey. To avoid selection bias towards high functioning individuals, we employ Heckman's two-step procedure as well as a more robust semiparametric alternative to ensure consistency.

Our empirical investigation is based on a conceptual framework in which fraudsters exploited elder per Becker (1968)'s rational choice theory of crime. As the waning cognitive

[1]Elder fraud/exploitation, defined as the illegal or improper use of an older adult's funds or assets, is recognized by the Centers for Disease Control and Prevention as a serious public health problem (Burnes et al., 2017). The financial victimization rate among older adults in the U.S., according to Hancock et al. (2025) and Ebner et al. (2023), is about 5–17% annually, with total losses from such frauds exceeded \$28 billion alone as of 2025.

ability breeds risk-taking behaviors and leads elders to adopt fintech beyond the optimal level, retained literacy curbs risks—until the nonlinear erosion diminishes it. We show that the interplay of these two forces, termed the "perception risk factor (PDF)", yields a U-shaped pattern in fintech adoption and fraud as decline deepens. We employ the HRS core panel from 2002-2022 to estimate the nonlinear erosion of financial literacy by cognitive decline and test the U-pattern with a cross-sectional sample in 2022 with fintech and fraud data.

We establish several important facts, some of which are new. First, while aggregate literacy erodes 1% annually via cognitive decline, the individual path varies: 15% show no decline whereas 25% declines over 50%. Second, consistent with prior studies[2], we find cognitive impairment still a key risk factor for elder financial exploitation in the digital age. However, the relationship may not be monotone and, in fact, depends on the parameters in the financial literacy erosion (e.g, the initial/residual levels, rate of decline, etc.), generating three phases of cognitive decline. Third, contrary to the conventional belief that fraud is heavily skewed toward vulnerable elders who are cognitively impaired, socially isolated, and with lower levels of financial/digital literacy, we find educated, wealthy, literate elders face higher fintech risks from overconfidence.

This study contributes to two streams of literature. First, there is interdisciplinary literature on elder Fraud Exploitation (FE): Psychology emphasizes cognitive vulnerabilities like decline in executive function and emotional biases, as in Spreng et al. (2017) on neuropsychological correlates and Lichtenberg et al. (2016) on decision-making scales. Economists model FE as asymmetric information problems, where perpetrators exploit trust. A seminal report is the MetLife Mature Market Institute (2011) study, quantifying FE costs and linking it to economic insecurity in retirement. Lusardi et al. (2017) highlight how low financial literacy correlates with exploitation, using economic models to show literacy's protective role against suboptimal choices. Gerontology links FE to health and isolation, per Acierno et al. (2010)'s mistreatment study and Pillemer et al. (2016)'s review, whereas criminology applies victimization theories like RAT, as in Burnes et al. (2017) and Goergen and Beaulieu (2010). Interdisciplinary calls for unified approaches appear in Bonnie and Wallace (2003), advocating technology and policy to prevent harm.

A growing economic literature on cognitive decline in older adults also focuses on how age-related impairments increase susceptibility to financial exploitation. Seminal studies include Ameriks et al. (2023) and Mazzonna and Peracchi (2024), which show older adults often underestimate their cognitive decline, resulting in financial losses and heightened fraud

[2]See, Burnes et al. (2017), Dong et al. (2011), Mosafer et al. (2025), Weissberger et al. (2020) and Yang et al. (2025).

risk due to poor decision-making. Agarwal et al. (2009) models life-cycle financial mistakes, finding a U-shaped pattern where cognitive decline in later life amplifies errors and vulnerability to exploitation, advocating regulatory interventions like advance directives. Angrisani and Lee (2019) uses HRS data to link cognitive declines to wealth reductions in households, implying increased fraud exposure from delayed control transfers. Overall, the literature calls for policies like education and fiduciary safeguards to mitigate these risks in aging populations.

2 Cognitive Decline and Financial Vulnerabilities

2.1 Conceptual Framework

To illustrate the effects of cognitive decline on fintech adoption and the consequences of misperception for fraud vulnerability, we present a conceptual framework that builds on Becker (1968)'s rational choice theory for offenders and Simon (1957)'s bounded rationality for victims. Here we provide the main intuitions and offer more details in Appendix A.

Key Intuitions Consider two agents in a sequential game: the elder (E) and the fraudster (F). Due to aging and the ensuing cognitive overload, E operates under bounded rationality and chooses e to maximize the "perceived utility" $U_E = b(e) - \pi_p L$, where $b(e)$ is the concave benefit function capturing fintech convenience, L is the loss if exploited, and $\pi_p = \pi(1-\phi\cdot\delta)$ is the perceived fraud probability which underestimates the true fraud probability π by a "perception discount factor" (PDF): $\equiv 1-\phi\cdot\delta$. The downward perception bias is due to cognitive decline δ and financial literacy ϕ, both normalized to $[0,1]$. After observing E's adoption level e, F, who acts rationally, decides whether to attempt fraud based on his expected utility as per Becker (1968).

A key insight here is that cognitive decline alone does not determine financial vulnerability or poor decision-making; instead, its effects are "weighted" by how much literacy persists[3]. By subtracting the literacy-weighted cognitive decline (e.g., $\phi\cdot\delta$), the PDF represents the residual or unmitigated risk—the portion of potential vulnerability not "absorbed" or compensated by literacy amid decline. Our model captures the convolution of cognitive decline

[3]To see this, note that

$$1-\phi\cdot\delta = (1-\phi)\cdot 1 + \phi\cdot(1-\delta) \tag{1}$$

Consider ϕ representing the proportion of financial decisions E tries to handle independently. The illiterate portion $1-\phi$ is the portion of decisions delegated to others. Assume that the cognitive decline δ only causes a downward bias on the portion that E handles independently, the PDF captures the overall cognitive bias on fraud risk.

δ and the financial literacy ϕ through the nonlinear PDF. While no academic literature uses the exact phrase "literacy-weighted cognitive decline," the formulation is supported by related concepts in behavioral economics, gerontology, and neuropsychology. Studies (Boyle et al., 2013, Li et al., 2015, Stewart et al., 2018, Tang, 2021) often model cognitive decline's effects on financial outcomes as mediated or moderated by literacy, using interaction terms in regressions or path analyses that parallel the product form.

For older adults, financial literacy ϕ decreases with age-related cognitive declines δ. We model such dependency via a decreasing Sigmoid-shaped function

$$\phi(\delta) = \frac{\phi_0}{1 + e^{k(\delta - \delta_0)}} + \phi_1 \tag{2}$$

In this formulation with $k < 0$, as cognitive decline gradually starts from 0 to 1, financial literacy declines at a nonlinear rate from $\phi_0 + \phi_1$ to ϕ_1, with the fast decline occurring at δ_0 (the inflection point).

We formally prove that the parameter set $(\phi_0, \phi_1, \delta_0, k)$ creates a financial literacy divide: (1) for those with a faster rate of decline k and lower retention of financial literacy (e.g., low values of ϕ_0, ϕ_1, δ_0), cognitive decline steadily reduces fintech engagement and thereby the fraud risk. That is, for low-literate older adults, retained financial literacy acts as a protective shield against fraud risk due to declined engagement. (2) for those with a slower rate of decline k and thereby higher sustained financial literacy, adoption and fraud risks both reverse at severe stage of cognitive decline, exhibiting a U-shaped pattern. That is, for high-literate older adults, overconfidence creates unforeseen vulnerability.

The weight of evidence suggests overconfidence is more prevalent among those with greater financial education. For instance, a recent meta-analysis (Jain et al., 2023) found that financially literate individuals were more likely to exhibit overconfidence in investment contexts, particularly when they perceived themselves as "experts." This led to behaviors like overtrading or underestimating risks (Inghelbrecht and Tedde, 2024).

Hypotheses Development The model generates several testable hypotheses.

- **H1** Fintech adoption declines continuously for low-literacy older adults but exhibits a U-shape pattern for high-literacy ones due to overconfidence.

- **H2** Overconfidence and Fraud Risk: Elders with high perceived control (overconfidence) despite objective decline are more fraud-prone.

- **H3** Protective Mechanisms: Higher baseline literacy or family support mitigates risks by closing the gap between perceived and actual abilities, reducing victimization.

These hypotheses guide our empirical analysis, testing how misperceived decline interacts with fintech to shape fraud landscapes.

2.2 Literature Review

The current literature provides supporting evidence for the conceptual framework of the three phases. While no single study explicitly replicates the model's phases, empirical and theoretical research on cognitive decline, financial literacy, fintech adoption, and fraud victimization in older adults reveals non-monotonic patterns that align with these dynamics, particularly modulated by literacy levels.

Studies show that early cognitive decline prompts risk aversion and reduced fintech engagement in lower-literacy groups, lowering adoption while initially curbing fraud exposure due to withdrawal from digital finance. Agarwal et al. (2009) document a U-shaped pattern in financial mistakes over the life cycle, with mild decline leading to suboptimal decisions and ambiguously affecting fraud (as lower exposure competes with emerging vulnerabilities). Similarly, Gamble et al. (2015) links mild cognitive impairment to decreased financial literacy and cautious behavior, decreasing adoption and fraud probability initially, but with ambiguous fraudster incentives due to mixed signals of vulnerability, especially prevalent in low-literacy populations where burden effects dominate without mitigation. Fujiki (2020), based on data in Japan, finds that low-literacy elders with mild decline avoid e-payments, aligning with cognitive burden effects and extending this phase across broader cognitive decline ranges for those with insufficient financial literacy.

The Vulnerability Amplification Phase is supported by evidence of escalating fraud risks as decline intensifies. Han et al. (2016) and Lambe et al. (2017) show neural correlates of increased scam susceptibility in moderate decline, where reduced adoption fails to offset rising exploitation for elders who engage sporadically but vulnerably. Han et al. (2021) report that moderate cognitive decline correlates with wealth losses and fraud victimization, as elders underestimate impairments, leading to persistent but vulnerable engagement. Mao and Liu (2022) find socioeconomic factors exacerbate fraud in mid-decline stages, with medium financial literacy amplifying vulnerability by encouraging partial adoption without robust guardianship.

The Resilience Recovery Phase finds backing in research on literacy's mitigating role in high-literacy groups, enabling recovery in adoption despite severe decline, though fraud risks rise. Lusardi et al. (2023) highlight that high financial literacy buffers decline, fostering resilient fintech use and utility gains in severe impairment, but warns of overconfidence increasing fraud exposure, aligning with phase III dynamics. Di Giacomo et al. (2023) describe a “resilience recovery” in digital affinity post-COVID, where cognitive reserve (proxied by high literacy) reverses adoption declines in severe impairment, boosting utility but elevating risks for literate elders. Peng et al. (2024) show digital finance enhances household resilience in severe crises, with high literacy driving recovery, though fraud incentives surge.

3 Data and Descriptive Analysis

This section proceeds as follows: We first describe the data sources, discuss sample selection and biases, define key variables, and present descriptive statistics stylized facts.

3.1 The HRS Data

This study utilizes data from the Health and Retirement Study (HRS), a nationally representative longitudinal survey of Americans aged 50 and older. The survey began in 1992 and is fielded biennially in even-numbered years. We draw from both the core interview file and the Leave-Behind Questionnaire (LBQ) file to capture a comprehensive profile of respondents' socioeconomic, health, and behavioral characteristics. A rotating subsample of 50% core respondents each year received the LBQ survey, which is self-administered and mailed back.

Note that the fintech adoption variables are available in the LBQ only from 2020. We therefore confine attention to the 2022 wave because the subsample rotation greatly limits the number of respondents who filed LBQ in both 2020 and 2022, invalidating any meaningful panel studies. To estimate the nonlinear erosion of financial literacy by cognitive decline, we retain the core survey from 2002 (wave 6) when the “Big Three Test” (Lusardi and Mitchell, 2006), our primary measure of financial literacy, was first incorporated. Our initial sample includes a panel of $n = 15303$ adults, observed on average for about 7 waves.

Key variables of interests are obtained from the LBQ file, encompassing experiences with financial fraud (e.g., reported victimization), adoption of fintech including online banking and insurance management, self-assessment of financial situation, and engagement with social network services (SNS). The core interview file includes detailed information on demographic controls such as age, race, gender, number of children, educational attainment, total assets, and self-reported health status, which are incorporated to account for potential confounding factors influencing financial behaviors and vulnerabilities. After merging with the LBQ file and removing missing values, the 2022 working sample consists of a cross-sectional sample of $n = 8654$ adults, 2829 of whom also completed the LBQ file.

Sample Selection While the HRS core file is widely-recognized as a nationally-representative dataset with rich and detailed information on older adults, the LBQ is much less so because the interviewers hand out the LBQ based on respondent profile rather than randomly. Table 1, which compares the sample mean between LBQ completers and non-completers in 2022[4], reaffirms the non-random selection because mean equality is rejected for every single variable except gender.

Specifically, LBQ completers have higher cognitive & financial literacy scores, possess greater assets, are highly educated, and report lower rates of poor health. These patterns suggest that LBQ completers represent a more advantaged, healthier, and digitally engaged subset of the broader HRS core sample, highlighting potential selection bias that could skew analyses toward underestimating risks or challenges in underrepresented groups. We discuss ways to correct for such bias in the Empirical Strategy section.

[Table 1 about here.]

3.2 Variable Definitions and Measures

Having established the sample, we now turn to the measurement of key variables to align with our conceptual framework and facilitate empirical tests.

Cognitive Decline δ Prior to 2020, the HRS constructed a summary score to measure overall cognitive functioning (McArdle et al., 2007), widely known as the Telephone Interview Cognitive Score (TICS)[5]. Following the same approach, we include questions from the HRS Core related to episodic memory, mental status, and vocabulary, as detailed in Table 2. Responses to these questions are combined to create a comprehensive cognitive score ranging from 0 to 33, with higher scores indicating higher cognitive ability.

[Table 2 about here.]

To ensure consistency with the conceptual model and facilitate empirical tests, we measure cognitive decline δ as the percentage decline from full literacy,

$$\text{Cognitive Decline } (\delta): \ = \frac{33 - \text{TICS cognitive score}}{33} \tag{3}$$

[4]According to Wiemers et al. (2024), the non-respondents in 2020 LBQ tend to be younger, non-White, less educated, unpartnered, employed, with more children, lower income/wealth, and poorer health.

[5]For economics and fince studies that use TICS, see Agarwal and Mazumder (2013), Banks et al. (2010), Choi et al. (2010), Fang et al. (2008), Mazzonna and Peracchi (2017), Rohwedder and Willis (2010), and Sloan (2024).

so that $\delta = 1$ means complete loss of cognition and $\delta = 0$ means full cognitive ability. Figure 1 depicts the distribution of cognitive decline by LBQ filing status. It can be seen respondents who completed LBQ suffer less cognitive decline overall.

[Figure 1 about here.]

Financial Literacy ϕ Numeracy Skills and Financial literacy are primarily measured by the respondent's score on the "Big Three" financial literacy test, with higher scores indicating greater numeracy skills & financial literacy. The original test consists of three multiple-choice questions developed by Lusardi and Mitchell (2006) to measure individuals' understanding of fundamental financial concepts: compound interest, inflation, and risk diversification.

Only the question on compound interest is incorporated in the 2022 HRS, proceeded by two numeracy questions. These three consecutive questions, which are used to assess how people use numbers in everyday life, can be found in Section D of the HRS core file. As opposed to multiple-choice questions, the user is supposed to enter responses manually in whole numbers.

Q178 If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?

Q179 If 5 people all have the winning numbers in the lottery and the prize is two million dollars, how much will each of them get?

Q180 Let's say you have $200 in a savings account. The account earns 10 percent interest per year. How much would you have in the account at the end of two years?

To ensure consistency with the conceptual model and facilitate empirical tests, we measure respondent's numeracy and financial literacy ϕ as (normalized) aggregate score from Q178-180 above,

$$\text{Financial Literacy } (\phi)\text{:} \quad = \frac{\text{score on Q178} + \text{score on Q179} + \text{score on Q180}}{3} \tag{4}$$

Financial Situation Since only the last question from the Big Three assesses respondent's numeracy in a finance context, we append the three questions with another two auxiliary questions from the LBQ file which measure respondents' self-assessment of financial situation:

Q25 (Perceived Control) Using a 0 to 10 scale where 0 means "no control at all" and 10 means "very much control," how would you rate the amount of control you have over your financial situation these days?

Q49 (Subjective financial well-being) I am securing my financial future.

1. COMPLETELY (Capitalized as displayed in the survey)
2. VERY WELL
3. SOMEWHAT
4. VERY LITTLE
5. NOT AT ALL

To be clear, neither question directly assesses financial literacy objectively. However, research indicates a positive association: higher financial literacy often correlates with greater perceived financial self-efficacy or control, as literate individuals feel more confident in managing finances, and this perception can mediate links to financial well-being. That said, perceptions can be inflated or biased (e.g., overconfidence leading to poor decisions despite low actual literacy), so the rating may not accurately mirror true literacy levels and could instead highlight psychological factors like self-efficacy or stress.

Fintech Adoption e We measure fintech adoption by respondents' usage of modern devices to do banking and buy/manage insurance. In the LBQ file, respondents are first asked, in Q38, whether they own & use any modern devices like laptop or tablet. Then they are asked, in Q38B1-B17, about if/how often do they use the modern device to participate in a list of 17 activities. As far as fintech concerns, we use Q38B2 and Q38B11:

B2 [How often do you] do banking, pay bills, send or receive money

B11 [How often do you] Buy or manage insurance online

1. DAILY
2. SEVERAL TIMES A WEEK
3. AT LEAST ONCE A MONTH

4. AT LEAST ONCE A YEAR
5. NEVER/NOT RELEVANT

To ensure the adoption rate is between 0 and 1 with an increasing scale, we normalize the answers for B2 and B11, respective,

$$\text{Online Banking/Insurance } (e)\text{:} \; = \frac{5 - \text{Answer to B2/11}}{5} \tag{5}$$

Fraud Victimization π The fraud risk π is derived from individuals' responses to the question: "Have you been the victim of fraud in the past five years?". [Discuss reverse causality]

To provide a first-cut elder fraud landscape, we compare the mean characteristics of LBQ respondents by fraud status.

[Table 3 about here.]

The summary statistics in Table 3 reveal that victims exhibit distinct profiles compared to non-victims, often characterized by greater digital engagement and socioeconomic advantages that paradoxically heighten vulnerability. Victims are more likely to use online banking (53.12% vs. 48.60%), online insurance (12.60% vs. 9.19%), Facebook (59.54% vs. 54.39%), and LinkedIn (15.71% vs. 12.17%), all with statistically significant differences ($p < 0.05$), suggesting that increased fintech and social media adoption exposes elders to scams through phishing or deceptive online interactions.

Victims report lower perceived control over finances (mean 7.22 vs. 7.86) and less confidence of securing their financial future (3.08 vs. 2.75), are slightly younger (67.55 vs. 69.08 years), more likely Black (23.92% vs. 19.20%), better educated (54.71% with college degrees vs. 45.97%), wealthier (mean assets $742,900 vs. $612,900), and in poorer self-reported health (6.87% poor vs. 4.17%), indicating that fraud disproportionately targets those with resources but potential overconfidence or health-related impairments. Interestingly, cognition scores show no significant difference (15.37 vs. 14.93, p=0.0715), implying fraud exploits behavioral rather than purely cognitive gaps. Overall, this underscores a landscape where digital inclusion amplifies risks for relatively capable elders.

3.3 Stylized Facts and Preliminary Patterns

The empirical patterns depicted in Figure 2 and 3 provide some empirical support for the non-monotonic relationship between cognitive decline, financial literacy, and fintech adoption outlined in our theoretical framework.

In Figure 2, online banking and insurance usage exhibit a generally downward trend across cognitive decline deciles, with adoption rates dropping sharply from higher levels in low-decline groups (decile 1) to near zero in severe-decline groups (decile 10). This aligns with Phases I and II of the model, where mild to moderate decline imposes a cognitive burden that discourages engagement due to heightened perceived risks and costs, as captured by the Perception Discount Factor (PDF). Notably, stratification by financial literacy reveals moderation effects: low-literacy groups ($\phi < 0.5$) show a steeper, more linear decline, indicating persistent disengagement and exclusion from fintech benefits, while high-literacy groups ($\phi > 0.5$) display fluctuations and a potential plateau or rebound in severe deciles, suggestive of Phase III resilience recovery driven by overconfidence. Figure 3 reinforces literacy's positive role, with adoption rising linearly from near-zero at literacy score 0 to significantly higher rates at score 3, underscoring how stronger numeracy and knowledge enable elders to navigate digital interfaces despite aging challenges.

These findings underscores fintech's dual-edged impact on financial inclusion and vulnerability. The rebound in adoption among high-literacy elders with severe decline implies that overconfidence—stemming from a convexly decreasing PDF—may expose them to amplified fraud risks, as they underestimate exploitation vectors like AI-generated scams while relying on protective features such as simplified apps. Conversely, low-literacy elders' continuous disengagement limits their access to financial markets and perpetuate reliance on costly traditional services.

[Figure 2 about here.]

[Figure 3 about here.]

In Figure 4 we visualize the relationship between cognitive decline δ and the associated erosion of financial literacy. The decline in numeracy and financial literacy as cognitive decline progresses often follows an S-shaped (sigmoidal) pattern, particularly in the context of neurodegenerative conditions like Alzheimer's disease (AD). This non-linear trajectory is characterized by three phases: slow initial decline during pre-clinical (e.g., $\delta < 0.3$), rapid acceleration during mild to moderate stages (e.g., $0.3 < \delta < 0.8$), and then deceleration or plateauing in severe stages as abilities bottom out near zero.

[Figure 4 about here.]

4 Empirical Strategy

This section outlines our empirical approach to estimate the retained financial literacy function ($\phi(\delta)$) and test the hypotheses on how cognitive decline (δ), moderated by financial literacy, influences fintech adoption (e) and fraud victimization, while addressing selection biases in the LBQ subsample.

4.1 Panel estimation of retained financial literacy $\phi(\delta)$

As noted above, the three phases of cognitive decline hinge on the path of retained financial literacy $\phi(\delta)$. Only the high literate elders — those whose literacy erodes slowly and remains relatively strong even at a high decline level—will transit to Phase II & III. This requires estimating the retained financial literacy function $\phi(\delta)$ and predicting how much literacy would have remained as cognitive decline worsens.

Motivated by the empirical joint distribution of ϕ and δ described in Figure 4, we estimate a nonlinear mixed-effect (NLME) which accounts for the non-linear relationship while handling the longitudinal structure. Consider a Sigmoid-shaped function of the form including individual heterogeneity (e.g., random intercepts) and demographic covariates $\mathbf{X}_{it}$:

$$\phi_{it} = \frac{\phi_0}{1 + \exp(-k(\delta_{it} - \delta_0))} + \boldsymbol{\beta}\mathbf{X}_{it} + u_i + \epsilon_{it} \tag{6}$$

where ϕ_{it} is the score on Lusardi's financial literacy test (e.g., the Big Three) of individual i in wave t, δ_{it} is $i's$ (cumulative) cognitive decline in wave t, $\mathbf{X}_{it}$ is a vector of demographic covariates such as age, race, eduction, etc., u_i is a time-invariant random effects capturing individual hetergeneity, ϵ_{it} is an unobservable error term assumed to be mean independent of the observable regressors. Here

- ϕ_0: the maximum literacy decline
- k: the steepness of the curve decline
- δ_0: the midpoint or inflection point (where the function reaches half its maximum)

and the covariate coefficients β are parameters to be estimated.

Of particular interest is the lower asymptote of the sigmoid function: $\phi_{1i} \equiv \boldsymbol{\beta}\mathbf{X}_{it} + u_i$, which can be interpreted as the residual financial literacy at maximum cognitive decline (e.g., δ approaches 1). To see this, note that ϕ_{it} approaches $\phi_0 + \phi_1$ and ϕ_1, respectively, when δ_{it} is near the left and right boundary. From the conceptual framework, the high literacy regime is defined by the condition

$$1 - 2\phi_1 \geq \phi_0[2s - ks(1-s)], \quad s \equiv \frac{1}{1 + e^{k(1-\delta_0)}} \tag{7}$$

To understand which elder will transit to Phase II & III, we must estimate $\phi_0, \phi_1, k, \delta_0$ to test the equation above.

The described NLME model extend linear mixed-effects models by allowing the mean function to be nonlinear in the fixed and random effect. Estimation is challenging because the likelihood involves intractable integrals over the random effects' distribution. Unlike linear models, where closed-form solutions exist, NLME requires approximations or numerical methods to maximize the (restricted) likelihood. We use Lindstrom and Bates (1990)'s algorithm which approximates the nonlinear model by linearizing it via first-order Taylor expansion around current estimates of fixed ($\hat{\beta}$) and random effects ($\hat{u}_i$). This transforms the NLME into an approximate linear mixed model, solvable using standard techniques. Specifically, the algorithm iterates: (1) Update fixed and random effects via penalized nonlinear least squares (PNLS) and (2) Update variance components via the linearized model using ML/REML[6], until convergence. We use a built-in command "**menl**" in Stata to execute the estimation.

4.2 Model Specification

To test hypotheses derived from the conceptual framework, we specify models that capture non-monotonic effects and incorporate the perception discount factor (PDF = 1 - $\phi(\delta) \cdot \delta$). We begin with ordinary least squares (OLS) regressions as a baseline, then employ a Heckman two-step selection model to correct for non-random participation in the LBQ, which is voluntary and self-administered, potentially biasing toward higher-functioning elders (e.g., those with better health, education, and cognitive abilities), as detailed below.

Fintech Adoption e We estimate the following equation, stratified by financial literacy levels:

$$e_i = \beta_0 + \beta_1\delta_i + \beta_2\delta_i^2 + \mathbf{X}_i\boldsymbol{\gamma} + \epsilon_i \tag{8}$$

where e_i is the fintech adoption rate (e.g., online banking or insurance management), δ_i is cognitive decline, the quadratic term captures potential non-linearity (e.g., rebound in Phase

[6] Maximum Likelihood (ML) vs. Restricted ML (REML): ML integrates over all parameters but can bias variance estimates downward in small samples. REML adjusts by focusing on residuals orthogonal to fixed effects, reducing bias.

III for high-literacy elders), and $\mathbf{X}_i$ is a vector of demographic controls.

To stratify the sample by financial literacy level, a person belongs to the high literacy regime if equation 7 holds. Based on the theoretically-derived hypothesis, we expect to find $\beta_2 > 0, \beta_1 < 0$, reflecting a U-shape relation. For low-literacy subsample, we expect to find $\beta_2 > 0, \beta_1 = 0$, representing a continuous decline across cognitive decline (extended Phase I). As an alternative check, we also drop the quadratic term to see if $\beta_1 < 0$.

Fraud Victimization We use a linear probability model for the binary outcome (victim in the past 5 years) to model the fraud dynamics,

$$\text{Fraud}_i = \beta_0 + \beta_1 \delta_i + \beta_2 \delta_i^2 + \beta_3 e_i + \beta_4 \text{PDF}_i + \boldsymbol{\beta}_5 (\delta_i \times \text{Big3}_i) + \mathbf{X}_i \boldsymbol{\gamma} + \epsilon_i \tag{9}$$

Here, the Big3 score (0–3) proxies literacy erosion for interactions, modulating the critical point of the quadratic function. We include additional variables such as perceived financial situation (e.g., securing financial future) and guardianship proxies (e.g., number of children, living with partner) to assess the psychological and behavioral mechanisms.

4.3 Addressing Selection Bias

The LBQ subsample is not random, as completers differ systematically from non-completers in the core sample (see Table 1). Non-response correlates with lower functioning (e.g., younger, non-White, less educated, lower wealth), leading to underreporting of vulnerabilities and inflated observed risks among completers (H4). To correct this, we use Heckman (1979) two-step procedure.

In the first stage, we estimate a probit model for LBQ participation:

$$\Pr(\text{LBQ}_i = 1) = \Phi(\mathbf{Z}_i \boldsymbol{\alpha}) \tag{10}$$

where $\mathbf{Z}_i \equiv [\mathbf{X}_i, \text{Time}_i]$ includes core demographics (age, race, gender, education, assets, health) plus an instrument: Interview time—specifically the duration of the core in-person interview—can serve as a valid exclusion restriction in Heckman's two-step selection model because it satisfies the key criteria for such an instrument: it affects the probability of selection into the subsample (completion of the voluntary Leave-Behind Questionnaire, or LBQ) but is assumed to be exogenous to the outcome variables of interest, such as fintech adoption or elder fraud victimization.

The core interview precedes the distribution of the LBQ, which is left behind for self-administration and mailing back, meaning longer interview durations may proxy respondent burden, fatigue, or availability, thereby reducing the likelihood of LBQ completion due to exhaustion or time constraints. This creates a testable relationship with nonresponse, as non-completers in the HRS tend to differ systematically (e.g., lower-functioning individuals like those with poorer health or lower education are less likely to respond). However, once selection is accounted for, interview time should not directly influence LBQ responses, as it is independent of the substantive content (e.g., financial behaviors or experiences) and does not correlate with unobserved factors driving those outcomes, assuming random variation in duration stems from procedural or interpersonal factors rather than the outcomes themselves.

Once Equation (10) is estimated, we compute the inverse Mills ratio:

$$\lambda_i = \phi(\mathbf{Z}_i\boldsymbol{\alpha})/\Phi(\mathbf{Z}_i\boldsymbol{\alpha}), \tag{11}$$

and included it in the second-stage OLS to correct for selection. This approach mitigates bias from unobserved factors (e.g., motivation, cognitive barriers) affecting both participation and outcomes, ensuring consistent estimates. The second-stage OLS coefficent of λ_i is therefore used to test the significance of sample selection.

5 Results

This section presents the empirical findings from our analysis, structured to align with the hypotheses outlined in Section 2. We begin with the effects of cognitive decline on the overall fintech adoption (H1), moderated by financial literacy levels, drawing on stratified regressions in Tables 5–6 (with fintech-specific outcomes in Tables 10–13). We then examine non-linear patterns in elder fraud victimization (H2 and H3), based on Tables 6–8, incorporating the perception discount factor (PDF) and protective mechanisms.

5.1 Panel Estimation of Retained Financial Literacy

The results from the mixed-effects nonlinear regression model are presented in Table 4, which quantify the pattern of financial literacy retention during cognitive decline. The model incorporates a sigmoid function described in Equation (6) to capture the nonlinear impact of cognitive decline δ. With an estimated inflection point δ_0 of 0.5255, we note the speed of financial literacy decline peaked during the mid-stage of cognitive decline. The maximum literacy decline $\phi_0 = 0.4031$, suggesting that the cumulative decline of financial literacy is nearly half.

[Table 4 about here.]

Results from the lower panel of Table 4 indicate notable patterns of financial literacy among demographic groups. As expected, education emerges as the strongest predictor of financial literacy — respondents with highschool and college degrees (or above) score 0.13 and 0.22 points higher than those who do not. Male, on average, score 0.11 points higher than female, which is consistent with the gender gap in financial literacy (Hasler and Lusardi, 2017, Yakoboski et al., 2020). Black Americans generally exhibit lower levels of financial literacy compared to other racial groups.

[Figure 5 about here.]

Figure 5 shows the distribution of ϕ_1, the retained financial literacy, in the 15303 older adults that we investigate. The graph highlights challenges in an aging population: most retain only moderate literacy (30-60%), potentially exacerbating retirement insecurity amid rising longevity and complex finances. The distribution is unimodal and positively skewed, indicating asymmetry where lower retention scores are more common, but a tail of higher performers pulls the mean upward. The highest frequency occurs around 30-35%, with roughly 700-800 observations, suggesting this is the most common retention level.

5.2 Cognitive Decline and Fintech Adoption

Tables 5 and 6 provide baseline evidence for H1, showing that cognitive decline generally reduces fintech adoption, but with heterogeneous effects by literacy strata. Low-literacy elders exhibit persistent disengagement: baseline OLS shows -0.3834*** (column 1), with Heckman at -0.3080*** (column 2), indicating steeper withdrawal. This supports the conceptual framework's Phase I (cognitive burden), where low-literacy individuals face persistent barriers, leading to monotonic declines without rebound. Adding controls, however, reduces the magnitude significantly.

[Table 5 about here.]

For high-literacy elders (Table 6), cognitive decline exhibits a nonlinear U-shaped impact, with a negative linear coefficient indicating initial reductions in adoption probability, but a positive quadratic term (0.6379 in column 1, strengthening to 1.0503* in Heckman column 2) suggesting rebounds at severe decline levels due to overconfidence. Adding controls (columns 3–4) preserves the signs but reduces magnitude and significance, suggesting confounders like education and assets partially mediate the effect. The degree of sample selection bias is milder for high-literacy individuals, as the inverse mill ratio coefficient λ is almost nonsignificant.

[Table 6 about here.]

5.3 Elder Fraud Victimization: Non-Monotonic Risks and Protective Factors

Table 7-8 present the empirical findings on the relationship between cognitive decline and elder fraud victimization, testing hypotheses H2 (overconfidence and fraud risk) and H3 (protective mechanisms), with a focus on non-linear dynamics and moderating factors. The dependent variable is a binary indicator for fraud victimization, estimated using OLS on the LBQ sample (columns 1 and 3) and Heckman selection models leveraging the broader HRS core data (columns 2 and 4) to correct for selection bias toward high-functioning respondents. All models include linear and quadratic terms for cognitive decline, interactions with numeracy scores, and fintech adoption variables, with additional controls (perceived control, guardianship proxies) in columns 3 and 4.

[Table 7 about here.]

[Table 8 about here.]

The results reveal a U-shaped pattern in fraud victimization with respect to cognitive decline, supporting H2. The linear term for cognitive decline is negative across all specifications, indicating an initial reduction in fraud risk as mild cognitive decline fosters risk aversion and disengagement from financial activities (Phase I of the conceptual framework). However, the positive quadratic term suggests a rebound in fraud risk at severe decline levels due to overconfidence and compensatory behaviors (Phase III). The Heckman adjustments amplify the quadratic effect (e.g., 0.3504* vs. 0.0828), reflecting a downward bias in OLS from excluding low-functioning individuals, as indicated by the significant inverse Mills ratio (lambda) of -0.1954*** (column 2) and -0.1748*** (column 4). After including additional controls in Table 8 does not materially affect the U-shaped pattern.

Interactions with numeracy test scores (NumT 1–3) provide insight into the moderating effect of financial literacy. The coefficients are generally small and mostly insignificant (e.g., 0.0266 to 0.0544 for OLS), but Heckman models show negative effects at higher numeracy levels (e.g., -0.1612** for NumT 3 in column 2), suggesting that higher numeracy may mitigate fraud risk in moderate decline but exacerbate it in severe cases when overconfidence emerges. In Figure 6, we plot the predicted fraud-cognitive relationship for individuals with different NumT scores. Higher level of financial literacy decreases the fraud probability while delaying the overconfidence regime.

[Figure 6 about here.]

Overall, the U-shaped pattern underscores that mild decline reduces fraud exposure, but severe decline, particularly among numerate individuals, heightens risks through overconfidence, modulated by fintech use and protective factors. Heckman corrections enhance reliability, with the inverse Mills ratio indicating a 17–19% bias correction.

5.4 Potential Mechanism: Psychological vs Behavioral

In the context of fraud risk amid cognitive decline, LRAT provides a situational lens to explain how psychological and behavioral mechanisms heighten vulnerability. These mechanisms map onto LRAT's core elements: They increase exposure (via routines), enhance target suitability (via perceived vulnerabilities), and reduce guardianship (internal or external). Empirical applications of LRAT to fraud, especially elder scams and cybercrimes, show it effectively predicts victimization by linking daily activities to risk, with cognitive decline acting as a key amplifier.

Psychological Mechanisms Psychological factors tie to LRAT by enhancing target suitability through perceived vulnerabilities (e.g., low control signals desperation) and influencing lifestyle choices that increase exposure. Impaired executive function promotes heuristic thinking, making individuals suitable targets per LRAT. This relates to perceived control, as low self-efficacy (a psychological mediator) reduces guardianship, heightening fraud during routines like online shopping. Psychologically, LRAT incorporates these as factors making targets more appealing, with perceived control/well-being mediating lifestyle risks.

To explore the potential mechanism behind the observed relationship, we include perceived control over financial situation & financial well-being in the model. Psychological processes in decline amplify fraud risk by distorting self-perception and emotional responses, with perceived control acting as a moderator. Slowed processing and executive deficits shift to heuristic thinking, impairing fraud resistance. Low perceived control exacerbates this, as financial self-efficacy mediates cognitive performance under scarcity, leading to poorer decisions and heightened vulnerability. In Column 5-6, we find that higher perceived control metrics (securing financial future, control over situation) are protective (-0.0792***, -0.0810***) and lower the overall fraud risk.

Behavioral Mechanisms Behavioral mechanisms align most directly with LRAT, as they encompass routines and lifestyles that facilitate convergence with offenders and absence of guardians. Living alone (behavioral) embodies absence of guardians, while SNS use extends routines into cyber-spaces, converging with fraudsters. LRAT applications to elder fraud highlight how isolated lifestyles amplify re-victimization. Behaviorally, LRAT centers on how routines (e.g., SNS, living arrangements) create opportunities for fraud, with cognitive decline reducing guardianship efficacy.

[Table 9 about here.]

Table 8 directly incorporates the PDF ($1 - \delta \cdot \phi$) and interactions, supporting overconfidence as a mechanism (H2): PDF is positively associated with fraud (0.031* in OLS, column 1; 0.079** in Heckman, column 2), implying misperceived risks drive victimization. Interactions with perceived control (overconfidence proxy) are positive (0.045* in column 3), while family support mitigates this (-0.028** in column 5), aligning with H3's protective role. Baseline literacy closes the perception-ability gap (-0.019 in column 6), reducing risks. These findings highlight fraud targeting overconfident, high-functioning elders, with PDF amplifying exposure by 3–8% per unit, robust to controls.

5.5 Robustness Checks

[Table 10 about here.]

[Table 11 about here.]

[Table 12 about here.]

[Table 13 about here.]

Tables 10-13 report regression results for fintech adoption (online banking and insurance) as a function of cognitive decline, moderated by financial literacy. Consistent with H1, adoption follows a non-linear pattern for high-literacy elders but is more linear and declining for low-literacy ones.

For high-literacy individuals, Table 10 shows that cognitive decline has a negative linear effect on online banking in baseline OLS (-0.4488, insignificant), but the quadratic term is positive (0.2366), suggesting a potential rebound at severe decline levels, aligning with Phase III overconfidence. Heckman corrections attenuate the linear coefficient to -0.6583* but strengthen the quadratic to 0.6108, with lambda negative and significant (-0.1211*), indicating selection bias toward higher-functioning respondents. Adding controls (columns 3–4) reduces magnitudes but preserves signs. Similarly, Table 12 for online insurance reveals stronger non-linearity: linear coefficients are negative and significant (-0.3371** in OLS, -0.5237*** in Heckman), while quadratic terms are positive (0.3464, rising to 0.6796** in Heckman), supporting resilience recovery via perceived compensatory tools.

In contrast, for low-literacy elders, Tables 11 and 13 show strictly linear negative effects, with no quadratic terms needed. Online banking declines significantly with cognitive decline (-0.3648*** in OLS, -0.3043*** in Heckman), and controls halve the effect (-0.1866***). For insurance, effects are weaker but still negative (-0.1179*** in OLS), becoming insignificant with controls (-0.0418), consistent with persistent disengagement (Phase I extension). Lambda is consistently negative and significant, underscoring underreporting biases in voluntary surveys like the LBQ (H4).

Table 13 verifies results using semiparametric estimation alongside OLS and Heckman. Cognitive decline maintains negative linear (-0.1609) and positive quadratic (0.0656) effects, though insignificant, with magnitudes between OLS and Heckman. Protective controls (perceived control: -0.0566*** to -0.0903***) and guardianship remain robust. Fintech effects are positive but smaller. This affirms the non-monotonic patterns are not model-specific. Additional checks (not shown) for alternative literacy thresholds and instruments (e.g., interview time) yield similar results, addressing endogeneity and underreporting.

6 Conclusion

This paper has explored the intricate interplay between cognitive decline, fintech adoption, and elder financial fraud through a novel conceptual framework and rigorous empirical analysis using HRS data. Our findings challenge conventional narratives by demonstrating that fintech acts as a double-edged sword: while it expands vulnerabilities for older adults, it also equips them with protective mechanisms that can attenuate risks, particularly for those with higher baseline financial literacy.

Empirically, we confirm Hypothesis 1: fintech adoption exhibits a non-monotonic, U-shaped pattern among high-literacy elders, with initial declines giving way to rebounds driven by overconfidence in compensatory tools, whereas low-literacy individuals experience persistent linear disengagement. For fraud victimization (Hypotheses 2–3), results reveal a U-shaped relationship with cognitive decline, amplified by fintech engagement but mitigated by accurate risk perceptions (via the perception discount factor) and guardianship factors like family networks. Selection corrections (Hypothesis 4) via Heckman models underscore that underreporting biases inflate observed risks among higher-functioning respondents, emphasizing the need for robust data strategies in future studies.

These patterns align with related research on cognitive misperception (Mazzonna and Peracchi, 2024), where unaware elders suffer greater wealth losses from poor decisions rather than rational disinvestment. Our robustness checks, including semiparametric estimations, affirm the non-linearity and highlight fintech's equalizing potential when paired with literacy-enhancing interventions.

The implications are profound for policy and practice. Regulators should prioritize AI-driven safeguards in fintech platforms to bridge literacy gaps and reduce underestimation of risks, such as mandatory simplified interfaces or real-time fraud alerts. Educational programs targeting digital-financial literacy could prevent overconfidence-driven rebounds, while incentives for family guardianship might close protective voids. Future research should extend to longitudinal fintech-specific datasets and emerging AI threats to better inform inclusive aging policies. Ultimately, by addressing misperception and selection biases, we can harness fintech's benefits to foster resilient financial ecosystems for older populations, curbing the $28 billion annual toll and promoting equitable inclusion.

[Table 14 about here.]

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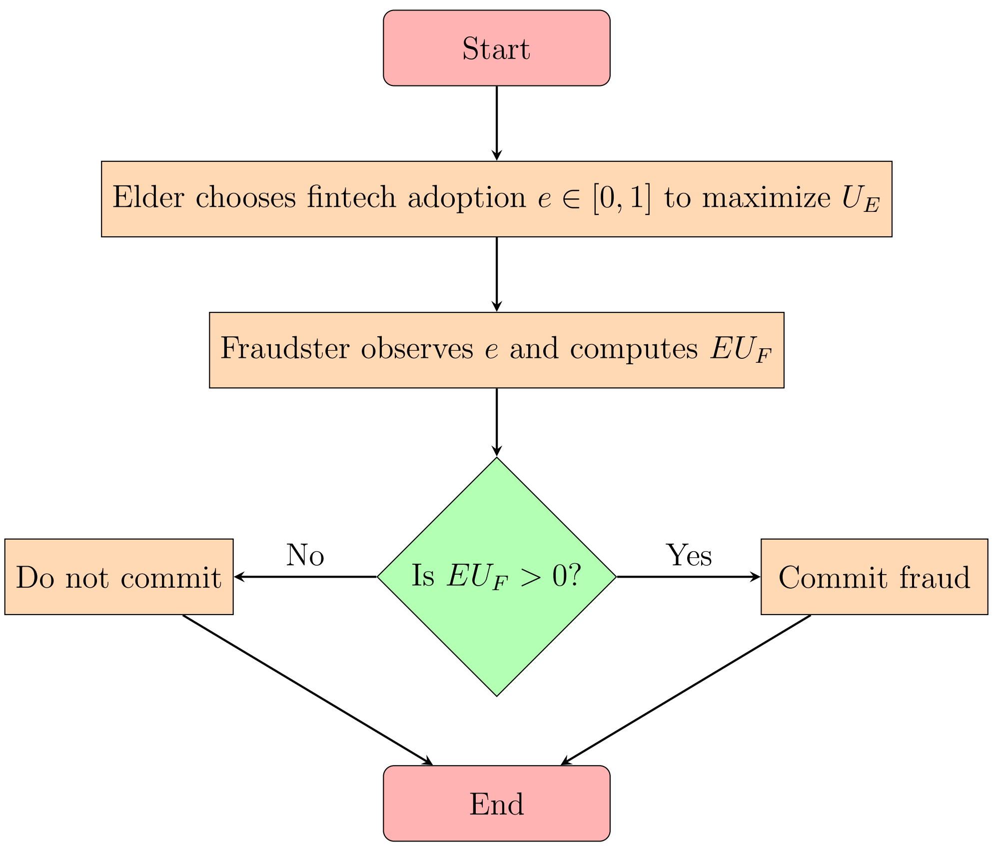
Appendix A Detailed Conceptual Model

To study the impact of fintech exposure on elder financial exploitation, we develop an economic model integrating Becker (1968)'s rational choice model of crime (for fraudsters), bounded rationality (for elders' decision-making under cognitive constraints), and cognitive decline (affecting elders' risk perception and fraud detection).

The economic model is a static optimization framework with two agents: the Elder (E) (potential victim) and the Fraudster (F) (offender). E chooses fintech adoption e to maximize her utility under bounded rationality, while F decides whether to attempt exploitation based on expected utility.

Sequential Game of Elder Financial Exploitation



A.1 Elder's Decision (Bounded Rationality with Cognitive Decline)

Fintech exposure, denoted by $e \in [0, 1]$, represents the elder's adoption level of fintech, ranging from no use ($e = 0$, e.g., avoiding online banking) to full engagement, offering convenience benefits that rise with e but simultaneously heighten exploitation opportunities like phishing or scams. To be specific, E chooses e to maximize her perceived utility

$$U_E = b(e) - \pi_p L \tag{12}$$

where π_p is the perceived risk of exploitation, L is financial loss (e.g., stolen fund), and $b(e)$ the convenient benefit of fintech.

The degree of E's cognitive decline is parameterized by $\delta \in [0, 1]$, where higher δ indicates greater decline, impairing risk perception and detection ability. Let $\pi = \delta e^2$ denotes the true fraud success probability (e.g., fraud is attempted and succeed), which inceases with both δ (cognitive decline further elevates fraud success probability by diminishing detection capabilities) and e. The fraud success probability $\pi = \delta e^2$ being convex in e implies that marginal increases in fintech adoption lead to accelerating fraud risks.

The theory of bounded rationality, pioneered by Herbert Simon, posits that individuals do not make fully optimal decisions due to inherent limitations in information processing, time, and cognitive capacity. Instead, they "satisfice" (settle for good-enough outcomes) using heuristics or simplified rules. In the context of aging, cognitive decline further bounds rationality, leading to suboptimal financial choices, such as underestimating fraud risks.

Our model captures this aspect by treating cognitive decline as a dynamic constraint that erodes financial literacy, resulting in a discounted perception of risk. To be precise, the perceived exploitation risk π_p is,

$$\begin{aligned} \pi_p &= \pi(1 - \phi(\delta) \cdot \delta) && (13) \\ \text{where} \quad \phi(\delta) &= \frac{\phi_0}{1 + e^{k(\delta - \delta_0)}} + \phi_1 && (14) \end{aligned}$$

where $\phi \in [0, 1]$ represents E's financial literacy with higher ϕ indicating greater literacy. The sigmoid function[7] above is monotonically decreasing, reflecting the negative correlation between cognitive decline and financial literacy. ϕ_1, the lower asymptote of the function, is the residual financial literacy (at maximum cognitive decline), ϕ_0 is the difference between peak literacy (at $\delta = 0$) and the residual level (at $\delta = 1$), and δ_0 is the inflection point where the decline of ϕ is the steepest.

This formulation aligns with bounded rationality's emphasis on cognitive constraints

[7]Note that this formulation allows the decline in financial literacy to be very mild at the boundries (e.g., δ near 0/1), which mirror the description of Figure X. Basically, these three parameters capture the nonlinear dependence between finanical literacy and cognitive decline: as cognitive decline starts gradually from 0 to 1, the person's financial literacy declines at a nonlinear rate from $\phi_0 + \phi_1$ to ϕ_1, with the fast decline happening at δ_0.

driving deviations from perfect rationality—here, the sigmoid form reflects nonlinear bounds (e.g., gradual early erosion accelerating later), and the underestimation proxies heuristic shortcuts or biases like overconfidence that ignore full risks.[8]

A.2 Fraudster's Decision (Becker Rational Choice)

The fraudster (F), who operates under full rationality as per Becker (1968)'s framework, committing fraud only if expected utility surpasses legitimate alternatives (normalized to zero). F's expected utility EU_F from attempting fraud is:

$$EU_F = \pi \cdot U_F(L - E) + (1 - \pi) \cdot U_F(-E) \tag{15}$$

where π is the fraud success probability, L is the offender's monetary reward from successful fraud (e.g., stolen funds), and $E = E(\delta)$ is the monetary equivalent of the time and resource needed to commit fraud (e.g., scouting targets, building trust, and applying coercion), which decreases with E's cognitive decline δ (e.g., $dE/d\delta < 0$).

Provided that the marginal utility of the offender $EU'_F(\cdot)$ is positive, it is easy to show that

$$\frac{\partial EU_F}{\partial \pi} = U_F(L - E) - U_F(-E) > 0 \tag{16}$$

$$\frac{\partial EU_F}{\partial L} = \pi_i U'_F(L - E) > 0 \tag{17}$$

That is, a more vulnerable target (with greater success probability π) or higher potential gain (with higher L) makes F more likely to attempt the crime.

A.3 Solving the Model

The model can be interpreted as a sequential equilibrium framework. E acts as the "leader" and chooses the fintech adoption level e first, maximizing their perceived utility under bounded rationality and cognitive decline (as detailed in the Elder's Decision section). The first order condition of E's utility (12) is

$$\frac{\partial U_E}{\partial e} = b'(e) - 2[1 - \phi(\delta) \cdot \delta]\delta e L. \tag{18}$$

[8]The weight of evidence suggests overconfidence is more prevalent among those with greater financial education. For instance, a recent meta-analysis (Jain et al., 2023) found that financially literate individuals were more likely to exhibit overconfidence in investment contexts, particularly when they perceived themselves as "experts." This led to behaviors like overtrading or underestimating risks (Inghelbrecht and Tedde, 2024).

Thus, $b'(e) = 2[1-\phi(\delta)\cdot\delta]\delta eL$. This implicitly defines $e^*(\delta)$, the optimal fintech adoption level of E. The theorem below gives the conditions under which e^* is monotonically decreasing in δ.

Theorem A.1. *(**Optimal Fintech Adoption** $e^*(\delta)$) Assume the benefit function $b(e)$ is increasing and concave ($b'(e) > 0$, $b''(e) < 0$ for $e \in (0,1)$). E maximizes perceived utility $U_E = b(e) - \pi_p L$, where $\pi_p = \delta e^2(1-\phi(\delta)\delta)$ underestimates true risk $\pi = \delta e^2$ due to bounded rationality. If the sigmoid function parameters $(\phi_0, \phi_1, k, \delta_0)$ satisfy*

$$1 - 2\phi_1 \geq \phi_0[2s - ks(1-s)], \quad s \equiv \frac{1}{1+e^{k(1-\delta_0)}} \tag{19}$$

then $e^*(\delta)$ is monotonically decreasing in $\delta \in [0,1]$ ("low literacy regime": early/persistent literacy degradation). Otherwise, $e^*(\delta)$ is U-shaped (convex) in $\delta \in (0,1)$, with an interior minimum at $\tilde{\delta}$ where e^* decreases from 0 to $\tilde{\delta}$ and increases from $\tilde{\delta}$ to 1 ("high literacy regime": resilient/delayed degradation)

Proof. The goal is to determine the sign of the derivative of $e^*(\delta, \phi(\delta))$. Define the first-order condition of E's utility function as an implicit function:$F(e,\delta,\phi) = b'(e) - 2(1-\phi(\delta)\cdot\delta)\delta eL = 0$. Apply the implicit function theorem:

$$\frac{\partial F}{\partial e}\frac{\partial e}{\partial \delta} + \frac{\partial F}{\partial \delta} = 0 \tag{20}$$

Partial with respect to e implies $\frac{\partial F}{\partial e} = b''(e) - 2(1-\phi(\delta)\cdot\delta)\delta L < 0$ because $b'' < 0$. Partial with respect to δ implies $\frac{\partial F}{\partial \delta} = \frac{\partial}{\partial \delta}\left[-2(1-\phi(\delta)\cdot\delta)\delta eL\right] = -2eL\frac{\partial}{\partial \delta}\left[(1-\phi(\delta)\cdot\delta)\delta\right]$. Compute the derivative of the term:$\frac{\partial}{\partial \delta}\left[(1-\phi(\delta)\cdot\delta)\delta\right] = 1 - 2\phi(\delta)\delta - \delta^2\phi'(\delta)$ Thus $\frac{\partial F}{\partial \delta} = -2eL(1-2\phi(\delta)\delta - \delta^2\phi'(\delta))$, so

$$\frac{de^*}{d\delta} = -\frac{\frac{\partial F}{\partial \delta}}{\frac{\partial F}{\partial e}} = -\frac{-2eL(1-2\phi(\delta)\delta - \delta^2\phi'(\delta))}{b''(e) - 2(1-\phi\cdot\delta)\delta L} \tag{21}$$

Since $b''(e) < 0$ and $2(1-\phi\cdot\delta)\delta L > 0$, the denominator is negative. The sign depends on the numerator $l(\delta) = 1 - 2\phi(\delta)\delta - \delta^2\phi'(\delta)$.

The condition for non-monotonicity (U-shaped $e^*(\delta)$) is the existence of a $\tilde{\delta} \in (0,1)$ where $\frac{de^*}{d\delta} = 0$, which occurs when $l(\delta)$ crosses zero from positive to negative. Given $l(0) = 1 > 0$ and continuity, this holds when $l(1) < 0$, i.e.,

$$1 - 2\phi_1 \geq \phi_0\left[2s - ks(1-s)\right], \tag{22}$$

where $s = \frac{1}{1+\exp[k(1-\delta_0)]}$. If $\phi_1 \geq 0.5$, the left-hand side ≤ 0, and the inequality holds unconditionally (since the right-hand side is positive). If $\phi_1 < 0.5$, the left-hand side is positive, requiring $\phi_0 > \frac{1-2\phi_1}{2s-ks(1-s)}$ for non-monotonicity. When $\phi_1 \leq 0.5$, and $\phi_0 \leq \frac{1-2\phi_1}{2s-ks(1-s)}$, the inequality does not hold, implying $l(\delta) > 0, \forall \delta \in (0,1)$.

It can be shown that when $b(e)$ is quadratic (implying $b''' = 0$) or when the second derivative $|b''|$ is "large enough", $e^*(\delta)$ is globally convex in (0,1). Therefore, $\tilde{\delta}$ is a global mininum[9]. □

This theorem generates a pair of testable hypotheses, highlighting the interplay of financial literacy and cognitive ability in determining the fintech adoption e^*. First of all, the scenario of a monotonically decreasing optimal fintech adoption $e^*(\delta)$ arises under specific parameter conditions: low ϕ_0 (shallow amplitude of literacy drop), $\phi_1 \leq 0.5$ (low baseline literacy at severe decline), and low δ_0 (early inflection point for literacy degradation).

Hypothesis 1. When financial literacy falls quickly and remains subdued as δ increases from 0 to 1, reinforcing a path of early and persistent degradation, elders respond with uniform caution: steadily reducing fintech engagement.

The monotonic decline in $e^*(\delta)$ reflects a literacy path where protective knowledge erodes prematurely and insufficiently recovers. With low δ_0, the inflection occurs early, causing literacy to plummet at mild δ, curtailing any overconfidence that might otherwise encourage adoption. Low ϕ_0 ensures the drop is gradual but unrelenting, while $\phi_1 \leq 0.5$ anchors

[9]The general symbolic expression for $d^2e^*/d\delta^2$ (with arbitrary $b(e)$) is:

$$\frac{4Le\left[L(2\delta\phi-1)^2(2L\delta(\delta\phi-1)-eb'''(e)+b''(e))+(L(2\delta\phi-1)^2-\phi(2L\delta(\delta\phi-1)+b''(e)))(2L\delta(\delta\phi-1)+b''(e))\right]}{(2L\delta(\delta\phi-1)+b''(e))^3},$$

where the sign analysis confirms positivity when $b'''(e) = 0$, but may require additional constraints on $|b''(e)|$ if $b'''(e) \neq 0$ (e.g., $b'''(e) > 0$ could introduce regions where the numerator bracket becomes positive, violating convexity unless $|b''(e)|$ is large enough to dominate those terms). Specifically, assuming $b(e) = ke - \frac{c}{2}e^2$ with $k > 0$ and $c > 0$ (ensuring $b'(e) > 0$ for $e \in [0,1]$ and $b''(e) = -c < 0$), the explicit form is:

$$e^*(\delta) = \frac{k}{c + 2L\delta - 2\phi L\delta^2},$$

assuming parameters ensure the denominator ¿ 0. Then,

$$\frac{de^*}{d\delta} = -k\frac{2L - 4\phi L\delta}{(c + 2L\delta - 2\phi L\delta^2)^2},$$

$$\frac{d^2e^*}{d\delta^2} = k\frac{4\phi L(c + 2L\delta - 2\phi L\delta^2) + 2(2L - 4\phi L\delta)^2}{(c + 2L\delta - 2\phi L\delta^2)^3}.$$

The numerator $4\phi L(c + 2L\delta - 2\phi L\delta^2) + 2(2L - 4\phi L\delta)^2 > 0$ (as both terms are non-negative under model assumptions $\phi, L > 0$), and the denominator is positive cubed (or negative cubed if analyzed for sign consistency, but the overall expression remains positive). Thus, $d^2e^*/d\delta^2 > 0$ holds for all $\delta \in (0,1)$ without requiring $|b''(e)|$ (i.e., c) to exceed any specific threshold beyond $c > 0$.

literacy at a low level in severe decline, preventing "resilience recovery" phases seen in high-literacy scenarios. Economically, this path embodies a self-reinforcing cycle: early literacy loss heightens perceived cognitive burdens, prompting disengagement to avoid perceived complexities or risks, which in turn limits opportunities for literacy reinforcement through practical use.

A U-shaped pattern in optimal fintech adoption $e^*(\delta)$ emerges under conditions of high ϕ_0 (steep amplitude of literacy drop), $\phi_1 > 0.5$ (high baseline literacy at severe decline), and high δ_0 (late inflection point). This trajectory implies that

Hypothesis 2. When financial literacy remains relatively robust at mild cognitive decline δ, the fintech adoption dips temporarily before rebounding due to overconfidence or compensatory reliance on prior knowledge.

The U-shape in $e^*(\delta)$ is intrinsically tied to a literacy degradation path that is gradual and resilient: high δ_0 postpones the inflection, preserving literacy through mild δ and enabling a "cognitive reserve" effect where elders draw on accumulated knowledge to mitigate early burdens. High ϕ_0 ensures a sharper but later drop, while $\phi_1 > 0.5$ maintains a strong floor, allowing overconfidence to drive rebound adoption in severe decline. Economically, this path represents a double bind—early stability encourages measured caution (reducing e to balance perceived risks), but lingering literacy fosters illusionary competence later, prompting re-engagement without full risk awareness. Unlike the monotonic case's uniform avoidance, this dynamic aligns with behavioral finance findings where moderate impairments induce prudence, but severe ones amplify susceptibility through over-reliance on fintech, underscoring how parameter-driven paths can shift from protective to exploitable equilibria.

After observing or anticipating the elder's chosen e^*, F decides whether to commit the crime (attempt exploitation) based on their expected utility EU_F in the Becker rational choice framework (as in the Fraudster's Decision section). The fraudster commits if $EU_F > 0$. The following theorem shows that the behavior of the fraud success probability $\pi(\delta) = \delta[e^*(\delta)]^2$ and the fraudster's expected utility EU_F depends on the parameters governing the literacy degradation path.

Theorem A.2. *Assume the fraudster's utility function U_F in (3) satisfies $U_F' > 0$, $U_F'' < 0$, and $dE/d\delta < 0$.*

1. *In the low literacy regime (monotonic $\downarrow e$) defined in Theorem A.1:*
    - *$\pi(\delta) = \delta[e(\delta)]^2$ is monotonically decreasing in $\delta \in (0, 1)$.*
    - *$dEU_F/d\delta$ is ambiguous for all $\delta \in (0, 1)$.*

2. *In the high literacy regime (U-shaped e):*

   - $\pi(\delta)$ *is convex U-shaped, with interior minimum at* $\delta^* \in (0, \tilde{\delta})$ *where* π *decreases for* $0 < \delta < \delta^*$ *and increases for* $\delta^* < \delta < 1$.
   - EU_F *increases with* δ *for* $\delta^* < \delta < 1$; $dEU_F/d\delta$ *is ambiguous for* $0 < \delta < \delta^*$.

Proof. To find the sign of $\frac{d\pi}{d\delta}$ for $\pi = \delta e^{*2}$, we solve for the critical point by setting $\frac{d\pi}{d\delta} = e^{*2} + 2\delta e^* \frac{de^*}{d\delta} = 0$. This gives $e^* = -2\delta \frac{de^*}{d\delta}$. Substituting the expression for $\frac{de^*}{d\delta}$ and solving for $b''(e^*)$ yields:

$$b''(e^*) = 2L\delta(3\phi(\delta)\delta - 1 + 2\delta^2\phi'(\delta)).$$

Since $b''(e) < 0$, a critical point δ^* exists only if the right-hand side is negative at some $\delta \in (0, 1)$, i.e., $3\phi(\delta)\delta - 1 + 2\delta^2\phi'(\delta) < 0$.

Recall from the proof of Theorem 2.1 that $l(\delta) = 1 - 2\phi(\delta)\delta - \delta^2\phi'(\delta)$. The parameter condition for part 1 ($1 - 2\phi_1 \geq \phi_0[2s - ks(1 - s)]$, where $s \equiv \frac{1}{1+e^{k(1-\delta_0)}}$) ensures $l(1) \geq 0$. Since $l(0) = 1 > 0$ and $l(\delta)$ does not cross zero in (0,1) under these parameters (by continuity and the form of ϕ), $l(\delta) > 0$ for all $\delta \in (0, 1)$, implying $\frac{de^*}{d\delta} < 0$ (monotonically decreasing e^*). For part 2, the condition was not met, implying $l(1) < 0$, so by continuity, there exists at least one $\tilde{\delta} \in (0, 1)$ where $h(\tilde{\delta}) = 0$, with $l(\delta) > 0$ for $\delta < \tilde{\delta}$ (decreasing e^*) and $l(\delta) < 0$ for $\delta > \tilde{\delta}$ (increasing e^*), yielding a U-shape with minimum at $\tilde{\delta}$.

Part 1: Monotonic Decreasing Case Under the parameter condition, $l(\delta) > 0$ for all δ, implying $\frac{de^*}{d\delta} < 0$. The RHS of the equation for $b''(e^*)$ is positive for all $\delta \in (0, 1)$ because $3\phi\delta - 1 + 2\delta^2\phi' > (3\phi\delta - 1) + 2\delta^2\phi'$, and since $\phi' < 0$, but the condition ensures the expression does not go negative (e.g., the low ϕ_0, low δ_0 limit makes ϕ' less negative late, keeping it positive). Thus, no δ^* exists where $\frac{d\pi}{d\delta} = 0$. To determine the sign of $\frac{d\pi}{d\delta}$, note that as $\delta \to 0^+$, $e^* \to e_0$ where $b'(e_0) = 0$ (or boundary $e^* = 1$ if $b'(1) > 0$), but $\pi \to 0$, and the initial decrease in e^* makes the second term negative, dominating for small δ. By continuity and no zero-crossing, $\frac{d\pi}{d\delta} < 0$ for all $\delta \in (0, 1)$, implying π is monotonically decreasing. For $EU_F = \pi U_F(L - E) + (1 - \pi)U_F(-E)$, the derivative is:

$$\frac{dEU_F}{d\delta} = \frac{d\pi}{d\delta}[U_F(L - E) - U_F(-E)] - \frac{dE}{d\delta}[\pi U_F'(L - E) + (1 - \pi)U_F'(-E)].$$

The first term is negative (since $\frac{d\pi}{d\delta} < 0$ and $U_F(L - E) > U_F(-E)$), the second is positive (since $\frac{dE}{d\delta} < 0$ and the bracket is greater than 0), so the sign is ambiguous.

Part 2: U-Shaped Case Under the condition, e^* has a minimum at some $\tilde{\delta} \in (0, 1)$. The RHS of the $b''(e^*)$ equation can be negative in an interval $(0, \bar{\delta})$ where $\bar{\delta} < \tilde{\delta}$, because the non-monotonicity of e^* (driven by $h(\delta)$) ensures the term $3\phi\delta - 1 + 2\delta^2\phi' < 0$ for some δ (as $\phi' < 0$ amplifies negativity at higher δ, but the dip in e^* centers the minimum). By continuity, there exists at least one $\delta^* \in (0, \tilde{\delta})$ where the equation holds, with the RHS $= b''(e^*) < 0$. To show the sign change in $\frac{d\pi}{d\delta}$: For small $\delta < \delta^*$, the decrease in e^* ($\frac{de^*}{d\delta} < 0$) makes the second term negative, and the model's convexity in π (from the dip in e^*) ensures $\frac{d\pi}{d\delta} < 0$ initially. At δ^*, it is zero, and for $\delta > \delta^*$, as e^* approaches its minimum and then increases, the positive first term dominates (especially as $\frac{de^*}{d\delta} > 0$ later makes both terms positive), yielding $\frac{d\pi}{d\delta} > 0$. Continuity and the single minimum in e^* ensure π is convex with a unique minimum at δ^*. For EU_F, when $\frac{d\pi}{d\delta} < 0$ ($\delta < \delta^*$), the first term negative, second positive, sign ambiguous; when $\frac{d\pi}{d\delta} > 0$ ($\delta > \delta^*$), both terms positive, so $\frac{dEU_F}{d\delta} > 0$. $\square$

The theorem has significant economic implications for elderly financial security and the broader fintech ecosystem, particularly in aging societies where cognitive decline (δ) is prevalent. By establishing a convex, U-shaped relationship for fraud success probability (π) with respect to δ—decreasing initially before rising after a critical point δ^*—the theorem suggests that mild cognitive decline may temporarily reduce fraud risks (e.g., through cautious behavior or reduced fintech exposure), but severe decline reverses this, amplifying vulnerabilities. This non-monotonicity implies that fraudsters' expected utility (EU_F) surges in later stages, incentivizing targeted exploitation of highly impaired elders, leading to heightened economic costs such as lost savings, increased healthcare burdens from stress-induced health declines, and eroded trust in digital financial systems.

Hypothesis 3. The relationship between fraud victimization and cognitive decline varies by literacy degradation regime:

1. In low literacy regimes (parameters implying early/persistent degradation, e.g., low ϕ_0, $\phi_1 \leq 0.5$, low δ_0), victimization decreases monotonically with decline.
2. In high literacy regimes (resilient/delayed degradation, e.g., high ϕ_0, $\phi_1 > 0.5$, high δ_0), it follows a U-shaped pattern, decreasing initially then increasing.

The theorem also underscores literacy (ϕ)'s role in shifting δ^*, implying that investments in financial education could extend the "protective" low-π phase, promoting inclusive fintech growth while curbing crime externalities estimated at billions annually in elder fraud losses. Specifically, higher ϕ_0 (larger amplitude of literacy drop) shifts δ^* rightward, extending the protective low-risk phase by making the literacy drop more pronounced but allowing longer initial resilience. A higher ϕ_1 (stronger baseline literacy at severe decline) shifts δ^* rightward, thereby delaying vulnerability amplification through sustained knowledge buffers. A higher δ_0 (later inflection point) shifts δ^* to the right, postponing the risk turnaround by delaying literacy degradation. A higher k (steeper transition) shifts δ^* leftward, accelerating the minimum by sharpening the degradation, potentially compressing the protective phase.

Hypothesis 4. A higher literacy profile (e.g., higher baseline literacy ϕ_1, aptitude ϕ_0, inflection point δ_0, and lower decline rate k) shifts the fraud risk minimum δ^* rightward, extending the protective phase.

A.4 Comparative Statics

[Table 15 about here.]

The comparative statics, reported in the Table 15, outline three distinct phases of how cognitive decline (denoted as δ, ranging from mild to severe) interacts with financial literacy (ϕ), fintech adoption (e), and fraud risks for older adults. These phases only emerge in the "high literacy regime," where literacy degrades slowly and remains relatively strong even at higher decline levels—think of it as elders who start with solid financial knowledge and retain enough of it to adapt, but this resilience can backfire due to bounded rationality. In contrast, low-literacy elders might stay stuck in the first phase, with steady disengagement.

In Phase I (mild decline), elders notice subtle slips—like forgetting passwords or struggling with app interfaces. This creates a "Cognitive Burden": fintech feels more hassle than help, so they pull back to avoid mistakes. Bounded rationality hasn't fully kicked in yet—perceived risks align somewhat with reality, prompting protective withdrawal. This phase dominates for low-literacy elders, who disengage early and stay disengaged, avoiding risks but also fintech's upsides like easier access during isolation.

In Phase II (moderate decline with resilient literacy), decision-making slows, scam detection weakens, but literacy hasn't bottomed out. Elders still engage a bit with fintech (e.g., basic apps), but their partial knowledge creates blind spots—like trusting a fake banking alert because it looks familiar. Overconfidence creeps in; they think they're handling it, but fraudsters see easy prey. This is the danger zone where elders underestimate escalating risks (due to sigmoid literacy decline hitting its steep part), leading to "vulnerable amplification".

In Phase III (severe cognitive decline with resilient literacy), the elder's bounded rationality leads to increasing overconfidence or underestimation of risks, making fintech seem more appealing despite actual vulnerabilities: High residual literacy ($\phi_1 > 0.5$) acts as a "cognitive reserve," allowing the elder to leverage past knowledge for "compensatory" adoption. They perceive fintech tools as easier to use (e.g., AI interfaces reducing cognitive load). Counterintuitively, severe decline "overpowers" burdens because literacy buffers create an illusion of control—elders adopt more aggressively, feeling empowered by tools that equalize access, even as actual risks (π) rise. This aligns with behavioral economics: Overconfidence in high-literacy elders leads to perceived welfare gains, but potentially real losses.

Appendix B Semiparametric Sample Selection Model Estimation

We estimate a semiparametric sample-selection model on the subsample of LBQ completers as a robustness check. The semiparametric sample-selection model in the spirit of Heckman (1979) but without assuming joint normality of the disturbances. The latent selection and outcome equations are

$$\begin{aligned} \text{Selection Model} : LBQ_i &= 1\{X_i\pi + Z_i\theta > u_i\}, \\ \text{Outcome Model} : Fraud_i &= X_i\beta + \varepsilon_i, \quad \text{observed only if} \quad LBQ_i = 1, \end{aligned}$$

where X_i contains demographic controls and covariates (age, race, gender, education, assets, health, cognitive decline, fintech adoption, financial-literacy and guardianship proxies). Z_i augments X_i and includes interview duration ($Time_i$) as an exclusion restriction, and (u_i, ε_i) are unobserved disturbances. We observe $Fraud_i$ only for respondents with $LBQ_i = 1$.

To release the parametric joint-normality assumption we impose

$$E(u_i|Z_i, X_i) = 0,$$

and model the conditional mean of the outcome disturbance on the observed sample non-parametrically:

$$E(\varepsilon_i|Z_i) = G(\gamma Z_i),$$

for some unknown function $G(\cdot)$ and parameter vector γ.

The outcome equation can be written in the partially linear form

$$\begin{aligned} Fraud_i &= X_i\beta + G(\gamma Z_i) + \varepsilon_i^* \\ \varepsilon_i^* &= \varepsilon_i - G(\gamma Z_i), \quad E(\varepsilon_i^*|Z_i) = 0 \end{aligned} \tag{23}$$

Taking conditional expectations with respect to Z_i gives

$$E[Fraud_i|Z_i] = E[X_i|Z_i]\beta + G(\gamma Z_i) \tag{24}$$

Subtracting (24) from (23) yields the Robinson differenced equation

$$Fraud_i - E[Fraud_i|Z_i] = (X_i - E[X_i|Z_i])\beta + \varepsilon_i^*$$

By construction $E(\varepsilon_i^*|Z_i) = 0$, β can be consistently estimated by Ordinary Least Squares (OLS):

$$\hat{\beta} = \arg\min_b \sum_{i=1}^{n} \Big\{ \big(Fraud_i - \widehat{E}[Fraud_i \mid Z_i]\big) - \big(X_i - \widehat{E}[X_i \mid Z_i]\big) b \Big\}^2.$$

A convenient nonparametric choice for $E[\cdot|Z]$ is a kernel smoother. The Nadaraya–Watson estimator at z is

$$\widehat{E}[Fraud \mid Z = z] = \frac{\sum_{i=1}^{n} K_h(Z_i - z)\, Fraud_i}{\sum_{i=1}^{n} K_h(Z_i - z)},$$
$$\widehat{E}[X \mid Z = z] = \frac{\sum_{i=1}^{n} K_h(Z_i - z)\, X_i}{\sum_{i=1}^{n} K_h(Z_i - z)}.$$

where K_h is the Gaussian kernel function with h as the bandwidth:

$$K_h = \frac{1}{h}\phi(\frac{Z_i - z}{h}).$$

The empirical results are reported in Table 14.

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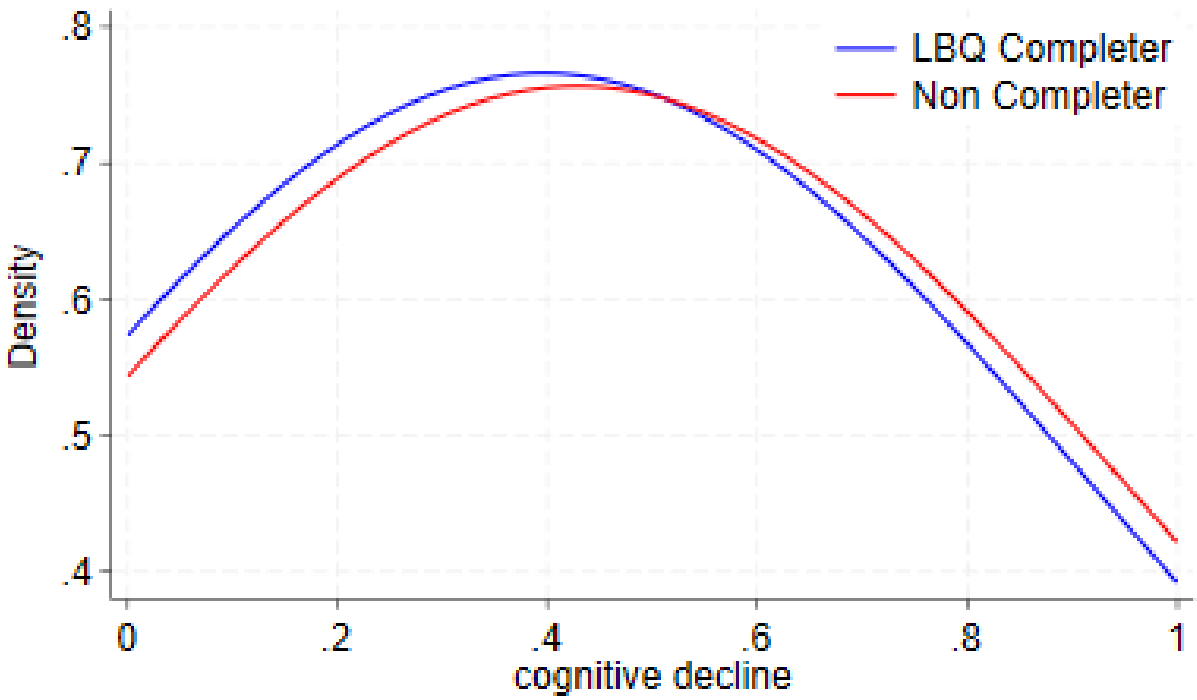
Figure 1: Distribution of cognitive decline by LBQ filing status



Note: This figure shows the density of cognitive decline defined in equation (3) in the HRS core sample, with the blue line indicating LBQ completer and red line indicating non-completers. The density is estimated via the Epanechnikov kernel.

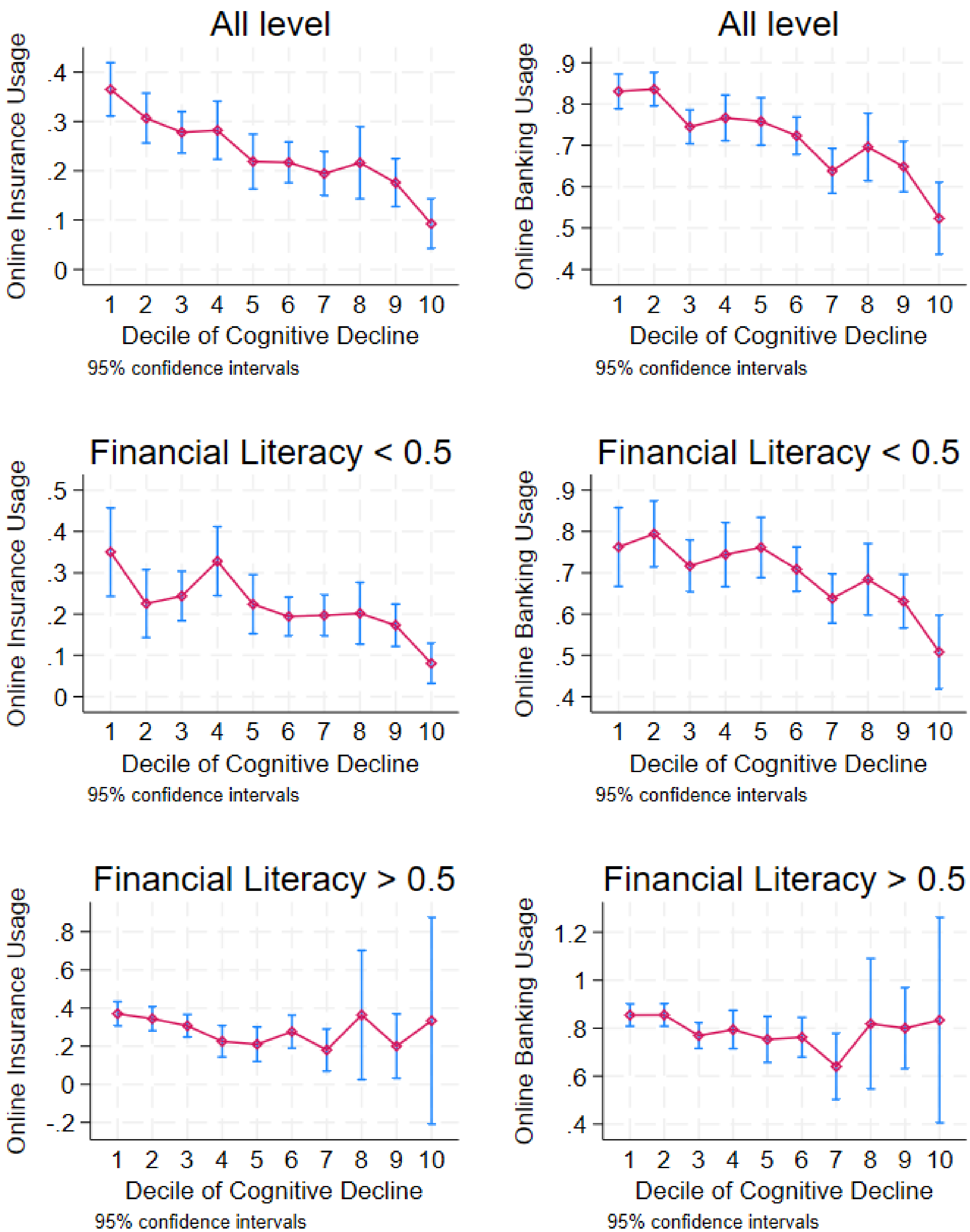


Figure 2: Title of the graph

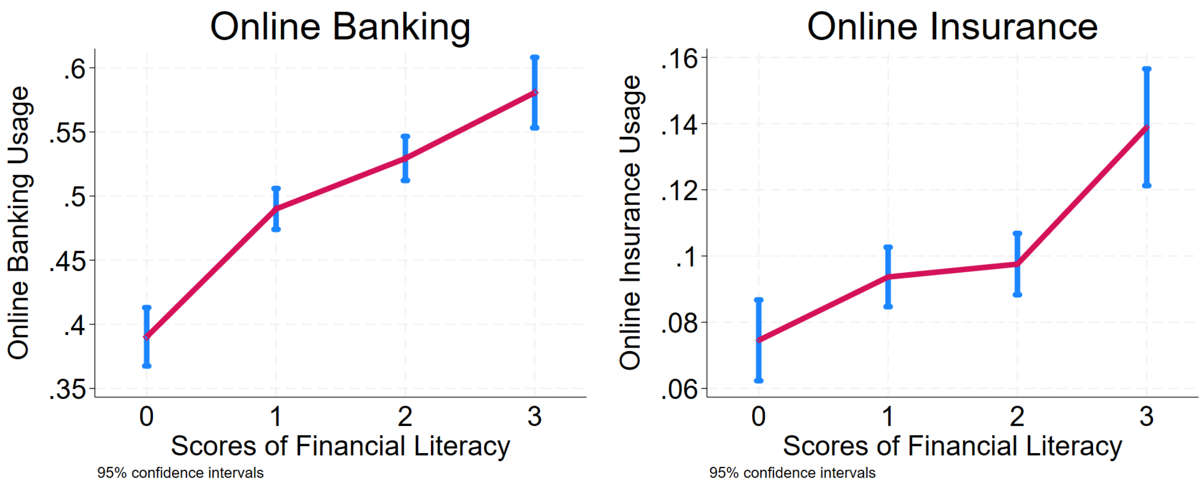
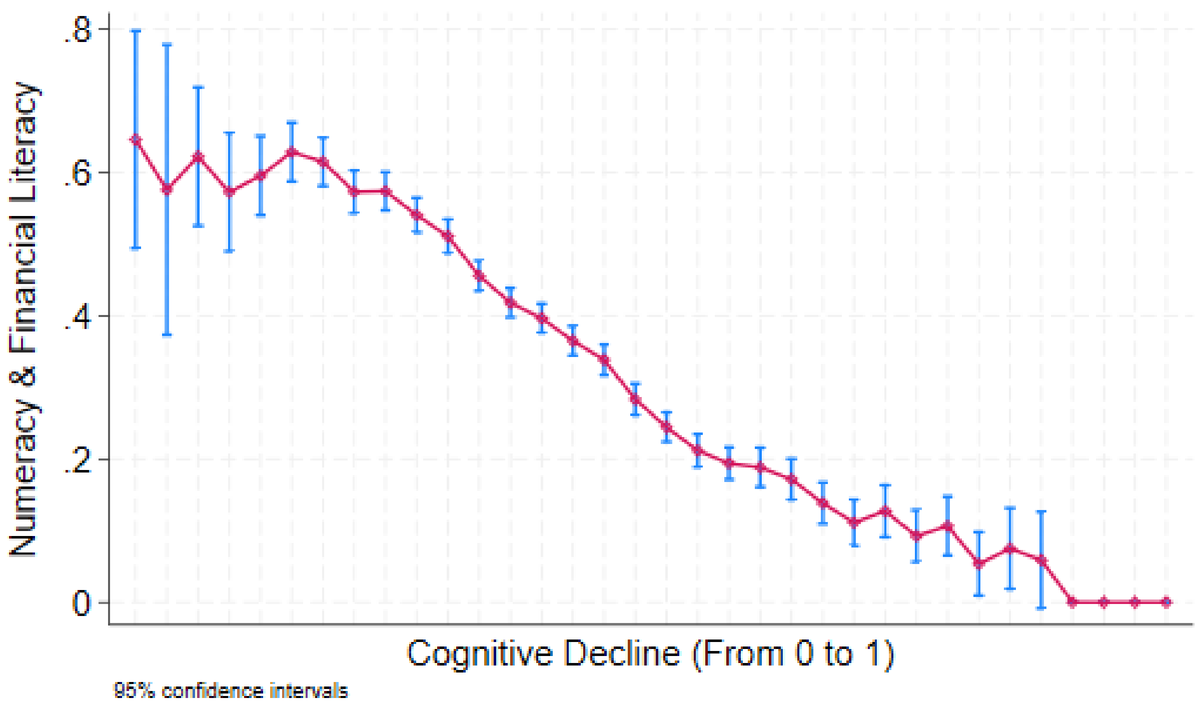


Figure 3: Title of the graph

Figure 4: The Eroded Financial Literacy as Cognitive Decline Progress



Note: This figure shows the sample mean of financial literacy ϕ at different values of cognitive decline δ, with the 95% CI as the blue bar around the mean. The sample includes all respondents in the 2022 HRS core file. As cognitive decline progresses from 0 to 1 along the horizontal axis, financial literacy decreases at a nonlinear rate, resembling a S-curve.

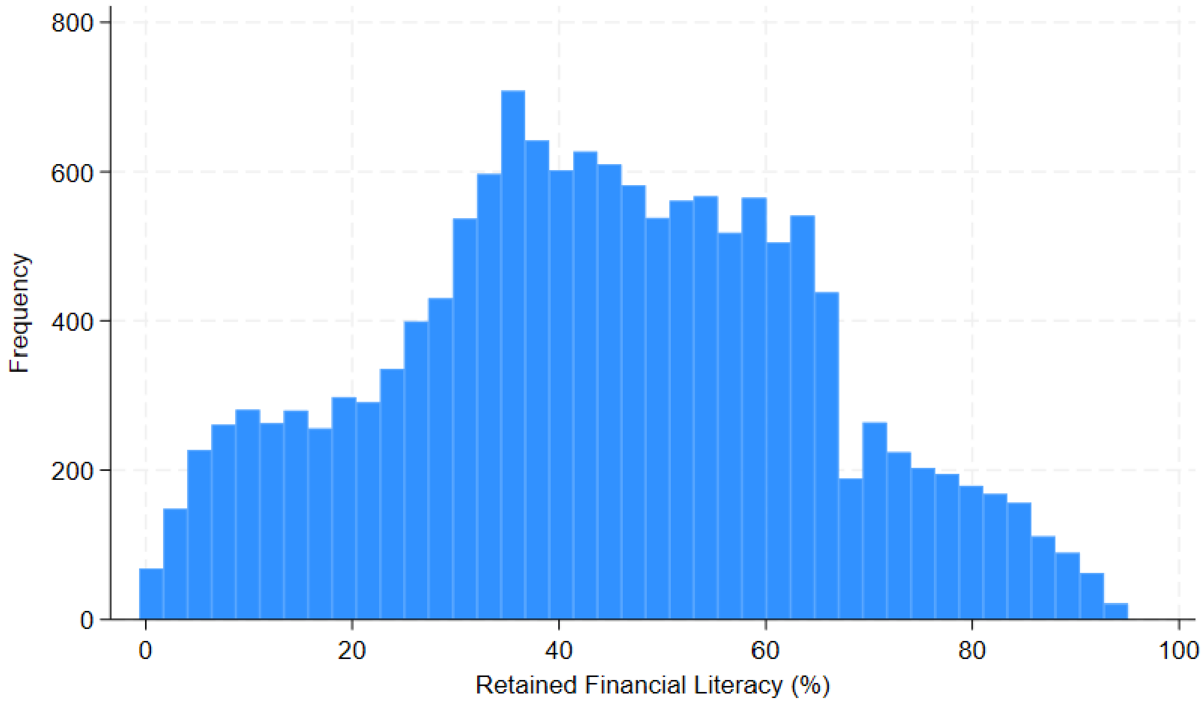


Figure 5: Distribution of ϕ_1, the retained financial literacy

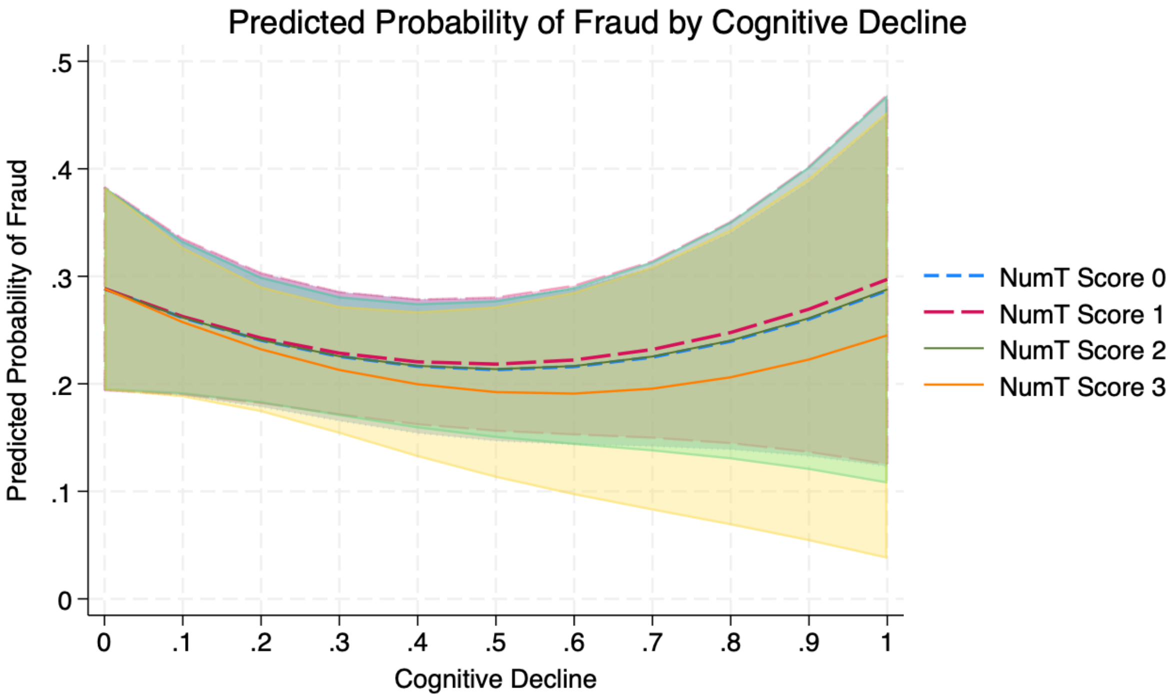


Figure 6: Predicted Probability of Fraud

List of Tables

Table 1: Characteristics of the LBQ and the HRS (2022) Core

	LBQ Completer		**Non-Completer**		
Variables	**Mean**	**Sd.Dev.**	**Mean**	**Sd.Dev.**	**P-value**
	μ_1	σ_1	μ_2	σ_2	$\mu_1 = \mu_2$
Cognition Score	19.8503	4.8273	18.7632	5.5236	0.0000***
Numeracy Test Score	1.2715	0.9096	1.0364	0.8720	0.0000***
Total Time (in hours)	2.6359	0.7091	2.2976	0.8262	0.0000***
Number of Children	2.8247	1.8763	2.9940	2.0748	0.0003***
Live with Partner	0.6100	0.4879	0.5257	0.4994	0.0000***
Age	73.0605	9.0088	70.2456	11.0510	0.0000***
Black	0.1854	0.3887	0.2925	0.4550	0.0000***
Male	0.4194	0.4936	0.4091	0.4917	0.3676
High School Degree	0.4577	0.4983	0.4301	0.4951	0.0166**
College Degree and above	0.4339	0.4957	0.3779	0.4849	0.0000***
Asset (in 1000K)	0.6412	1.3577	0.4502	1.0789	0.0000***
Poor Self-Reported Health	0.0446	0.2064	0.0721	0.2587	0.0000***
N	2692		5962		

Notes: This table reports means and standard deviations for selected characteristics of the HRS 2022 LBQ section and the Core section. The last column reports p-values from t-tests comparing the means between the two groups.

Table 2: Measurement of Cognitive Score

HRS Core 2022	Range
Immediate Word Recall	0-10
Delayed Word Recall	0-10
Serial 7s	0-5
Scissors	0,1
Cactus	0,1
President	0,1
Vice President	0,1
Date: Month	0,1
Date: Day	0,1
Date: Year	0,1
Date: day of week	0,1
Total	33

Note:
Immediate Word Recall: Respondents are read a list of 10 words and asked to recall as many as possible immediately. Score is the number of correct words recalled (0-10). *Delayed Word Recall*: After a delay, respondents are asked to recall the same 10 words. Score is the number of correct words recalled (0-10). *Serial 7s*: Respondents subtract 7 from 100 five times in succession. Score is the number of correct subtractions (0-5). *Scissors*: Object naming task where respondents identify the tool used to cut paper (correct answer: scissors). *Cactus*: Object naming task where respondents identify the prickly plant found in the desert (correct answer: cactus). *President*: Respondents name the current President of the United States. *Vice President*: Respondents name the current Vice President of the United States. *Month*: Respondents state the current month. *Day*: Respondents state the current day of the month. *Year*: Respondents state the current year. *Day of week*: Respondents state the current day of the week. For all questions above, scored 1 if correct, 0 otherwise.

Table 3: Summary Statistics by Fraud Status

Variables	Fraud = 1 Mean	Fraud = 1 Sd.Dev.	Fraud = 0 Mean	Fraud = 0 Sd.Dev.	P - value for Means equality
Cognition Score	20.8429	4.5576	19.7437	4.8442	0.0005***
Online Banking	0.5029	0.3128	0.4594	0.3254	0.0395**
Online Insurance	0.1073	0.1898	0.0798	0.1593	0.0095***
Control Financial Situation	7.2720	2.4836	7.9408	2.2220	0.0000***
Securing Financial Future	2.9808	1.1617	2.7018	1.1387	0.0002***
Numeracy Test Score	1.3793	0.8889	1.2600	0.9112	0.0440**
Number of Children	2.9080	1.7385	2.8157	1.8906	0.4500
Live with Partner	0.5594	0.4974	0.6154	0.4866	0.0780*
Use Facebook	0.5651	0.4109	0.4967	0.4395	0.0163**
Use Linkedin	0.1408	0.2511	0.0933	0.2273	0.0015***
Use Whatsapp	0.1293	0.2717	0.1442	0.2927	0.4325
Total Time (in hours)	2.8808	0.8326	2.6096	0.6896	0.0000***
Age	71.4023	9.7003	73.2386	8.9152	0.0017***
Black	0.2222	0.4165	0.1814	0.3854	0.1069
High School Degree	0.4368	0.4969	0.4599	0.4985	0.4765
College Degree and above	0.5096	0.5009	0.4258	0.4946	0.0094***
Male	0.3716	0.4842	0.4245	0.4944	0.1001
Asset (in 1000K)	0.8196	2.1259	0.6221	1.2466	0.0255**
Self Reported Health (Poor)	0.0613	0.2403	0.0428	0.2024	0.1684
N	261		2431		

Notes: This table reports means and standard deviations for selected characteristics by fraud victim status. The last column reports p-values from t-tests comparing the means between the two groups.

Table 4: Summary of Mixed-Effects Nonlinear Regression Results

Sigmoid Function Parameter	Coefficient	Std. Err.	z	$P > \|z\|$
δ_0 (inflection point)	0.5255	0.0177	29.70	0.000
k (speed of decline)	4.1034	0.2693	15.24	0.000
ϕ_0 (max literacy decline)	0.4031	0.0175	23.00	0.000
Demographic Parameter				
Age	0.0003	0.0001	2.61	0.009
Black	-0.1102	0.0038	-29.24	0.000
High school	0.1334	0.0044	30.58	0.000
College Degree and Above	0.2210	0.0042	52.40	0.000
Asset (in 1000K)	8.46e-09	8.54e-10	9.91	0.000
Male	0.1115	0.0032	34.95	0.000
Self Reported Health (Poor)	-0.0162	0.0049	-3.33	0.001

Notes: This table reports the nonlinear mixed-effect model with individual heterogeneity (e.g., random intercepts u_i) and demographic covariates $\mathbf{X}_{it}$,

$$\phi_{it} = \frac{\phi_0}{1 + \exp(-k(\delta_{it} - \delta_0))} + \boldsymbol{\beta}\mathbf{X}_{it} + u_i + \epsilon_{it}$$

, where ϕ_{it} is the score on Lusardi's financial literacy test (e.g., the Big Three) of individual i in wave t.

Table 5: Fintech Adoption at Lower Financial Literacy

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman
Quadratic Model				
Cognitive Decline	-0.1027	0.1799	0.2501	0.2974
	(0.3857)	(0.4213)	(0.3878)	(0.4025)
Cognitive Decline^2	-0.5329**	-0.5343**	-0.4513*	-0.4507*
	(0.3264)	(0.2850)	(0.3216)	(0.2633)
λ		-0.2756***		-0.1516***
		(0.0482)		(0.0385)
Lnear Model				
Cognitive Decline	-0.3834***	-0.3080***	-0.1608***	-0.1129*
	(0.0572)	(0.0622)	(0.0613)	(0.0636)
λ		-0.2745***		-0.1514***
		(0.0490)		(0.0384)
N	1821	6186	1821	6186
Demographic Control	No	No	Yes	Yes

Note: This table reports regression estimates of cognitive decline on lower financial literacy individuals. The dependent variable is a rescaled fintech adoption index combining binary indicators for online banking and online insurance. The models include only the linear term of cognitive decline. Columns (1) and (3) present OLS estimates using the LBQ sample, while columns (2) and (4) display results from Heckman selection models based on HRS core data to account for potential sample selection bias. Control variables include age, race, gender, education, asset holdings, and self-reported health status. The *lambda* coefficient in the Heckman models represents the inverse Mills ratio.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Fintech Adoption at Higher Financial Literacy

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman
Cognitive Decline	-0.9357**	-1.2059***	-0.7211*	-0.8884**
	(0.3857)	(0.4213)	(0.3878)	(0.4025)
Cognitive Decline^2	0.6379	1.0503*	0.6128	0.9447*
	(0.5264)	(0.5850)	(0.5216)	(0.5633)
lambda		-0.1136*		-0.0906
		(0.0682)		(0.0585)
N	788	1847	788	1847
Demographic Control	No	No	Yes	Yes

Note: This table reports regression estimates of cognitive decline on higher financial literacy individuals. The dependent variable is a rescaled fintech adoption index combining binary indicators for online banking and online insurance. The models include both linear and quadratic terms for cognitive decline to capture potential non-linear effects. Columns (1) and (3) report OLS estimates based on the LBQ sample, while columns (2) and (4) report results from Heckman selection models using HRS core data. Demographic control variables include age, race, gender, education, asset and self-reported health . The *lambda* coefficient in the Heckman models represents the inverse Mills ratio.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Non-linear Regression Results of Fraud

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman
Cognitive Decline	-0.2021	-0.3288*	-0.2418	-0.3663**
	(0.1718)	(0.1811)	(0.1727)	(0.1804)
Cognitive Decline^2	0.0828	0.3504*	0.0883	0.3250
	(0.1919)	(0.2066)	(0.1922)	(0.2044)
NumT Score 1 * Cognitive Decline	0.0266	-0.0063	0.0325	0.0045
	(0.0329)	(0.0348)	(0.0328)	(0.0343)
NumT Score 2 * Cognitive Decline	0.0146	-0.0549	0.0344	-0.0216
	(0.0421)	(0.0460)	(0.0424)	(0.0453)
NumT Score 3 * Cognitive Decline	0.0065	-0.1612**	0.0544	-0.0815
	(0.0711)	(0.0819)	(0.0719)	(0.0802)
Online Banking	0.0150	0.0111	0.0176	0.0159
	(0.0187)	(0.0186)	(0.0191)	(0.0190)
Online Insurance	0.0701*	0.0533	0.0566	0.0433
	(0.0368)	(0.0367)	(0.0371)	(0.0369)
Securing Fin. Future			-0.0557**	-0.0556**
			(0.0227)	(0.0225)
Control Fin. Situation			-0.0906***	-0.0903***
			(0.0276)	(0.0274)
SSN			0.0066	0.0036
			(0.0087)	(0.0086)
Number of Children			0.0043	0.0072**
			(0.0031)	(0.0033)
Live with Partner			-0.0254**	-0.0435***
			(0.0121)	(0.0131)
lambda		-0.1954***		-0.1748***
		(0.0377)		(0.0361)
N	2692	8654	2692	8654
Demographic Control	No	No	No	No

Note: The dependent variable is an indicator for fraud victimization. Columns (1) and (3) report OLS estimates based on the LBQ sample, while columns (2) and (4) report results from Heckman selection models using HRS core data. The specifications include both linear and quadratic terms for cognitive decline, and interaction terms with numeracy test scores (1–3). Fintech adoption, perceived control variables and guardianship proxies are included as controls in Columns (3) and (4). The *lambda* coefficient in the Heckman models represents the inverse Mills ratio. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Non-linear Regression Results of Fraud with Controls

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman
Cognitive Decline	-0.1868	-0.3070*	-0.1956	-0.2997*
	(0.1756)	(0.1810)	(0.1756)	(0.1795)
Cognitive Decline^2	0.1070	0.3453*	0.0957	0.2981
	(0.1943)	(0.2041)	(0.1944)	(0.2020)
NumT Score 1 * Cognitive Decline	0.0234	0.0113	0.0213	0.0102
	(0.0336)	(0.0344)	(0.0334)	(0.0339)
NumT Score 2 * Cognitive Decline	0.0218	-0.0082	0.0259	0.0009
	(0.0442)	(0.0456)	(0.0440)	(0.0450)
NumT Score 3 * Cognitive Decline	0.0172	-0.0763	0.0358	-0.0418
	(0.0746)	(0.0791)	(0.0744)	(0.0778)
Online Banking	0.0052	0.0039	0.0118	0.0118
	(0.0189)	(0.0188)	(0.0192)	(0.0191)
Online Insurance	0.0537	0.0412	0.0457	0.0363
	(0.0373)	(0.0370)	(0.0374)	(0.0371)
Securing Fin. Future			-0.0702***	-0.0705***
			(0.0237)	(0.0235)
Control Fin. Situation			-0.0839***	-0.0846***
			(0.0278)	(0.0276)
SSN			0.0003	-0.0008
			(0.0091)	(0.0091)
Number of Children			0.0058*	0.0084**
			(0.0032)	(0.0033)
Live with Partne			-0.0265**	-0.0455***
			(0.0128)	(0.0137)
lambda		-0.1464***		-0.1249***
		(0.0303)		(0.0282)
N	2692	8654	2692	8654
Demographic Control	Yes	Yes	Yes	Yes

Note: The dependent variable is an indicator for fraud victimization. The models include both linear and quadratic terms for cognitive decline, as well as interactions with numeracy test scores (1–3). All specifications include demographic controls. Demographic control variables include age, race, gender, education, asset and self-reported health. The *lambda* coefficient in the Heckman models represents the inverse Mills ratio. Standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Regression Results of Fraud

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman	(5) OLS	(6) Heckman
$1 - \delta * \phi$	0.3185***	0.2497***	0.3182***	0.2510***	0.3099***	0.2572***
	(0.0644)	(0.0662)	(0.0645)	(0.0663)	(0.0645)	(0.0657)
Online Banking			0.0116	0.0073	0.0102	0.0074
			(0.0187)	(0.0187)	(0.0191)	(0.0190)
Online Insurance			0.0509	0.0401	0.0479	0.0394
			(0.0371)	(0.0369)	(0.0374)	(0.0372)
SSN					0.0000	-0.0011
					(0.0091)	(0.0091)
Number of Children					0.0060*	0.0086***
					(0.0032)	(0.0033)
Live with Partner					-0.0279**	-0.0467***
					(0.0127)	(0.0136)
lambda		-0.1307***		-0.1274***		-0.1125***
		(0.0287)		(0.0288)		(0.0270)
N	2692	8654	2692	8654	2692	8654
Demographic Control	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is an indicator for fraud victimization. Columns (1), (3), and (5) present OLS estimates using the LBQ sample, while Columns (2), (4), and (6) report Heckman selection models estimated with HRS core data to account for potential sample selection bias. δ denotes cognitive decline, and ϕ denotes the (normalized) financial literacy and financial situation score. Columns (3) and (4) add controls for fintech adoption (online banking and insurance), while Columns (5) and (6) further include SSN usage and guardianship proxies (number of children, living with a partner). All specifications control for demographics, including age, race, gender, education, assets, and self-reported health. The *lambda* coefficient in the Heckman models represents the inverse Mills ratio. Standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Regression Results of Online Banking (Financial Literacy > 0.5)

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman
Cognitive Decline	-0.4488	-0.6583*	-0.2843	-0.3073
	(0.3277)	(0.3531)	(0.3259)	(0.3328)
Cognitive Decline^2	0.2366	0.6108	0.2172	0.2631
	(0.4568)	(0.5090)	(0.4486)	(0.4705)
lambda		-0.1211*		-0.0145
		(0.0678)		(0.0469)
N	1066	2829	1066	2829
Demographic Control	NO	NO	YES	YES

Note: This table presents regression estimates of cognitive decline on online banking usage among individuals with financial literacy above 0.5. The models include both linear and quadratic terms for cognitive decline to capture potential non-linear effects. Columns (1) and (3) report Ordinary Least Squares (OLS) estimates based on the LBQ sample, while columns (2) and (4) report results from Heckman selection models using HRS core data to address potential sample selection bias. Demographic control variables include age, race, gender, education, asset and self-reported health . The *lambda* coefficient in the Heckman models represents the inverse Mills ratio.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Regression Results of Online Banking (Financial Literacy < 0.5)

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman
Cognitive Decline	-0.3648***	-0.3043***	-0.1866***	-0.1535**
	(0.0572)	(0.0623)	(0.0626)	(0.0655)
lambda		-0.1313***		-0.0710*
		(0.0488)		(0.0408)
N	1626	5825	1626	5825
Demographic Control	No	No	Yes	Yes

Note: This table reports regression estimates of cognitive decline on online banking usage among individuals with financial literacy below 0.5. The models include only the linear term of cognitive decline. Columns (1) and (3) present OLS estimates using the LBQ sample, while columns (2) and (4) display results from Heckman selection models based on HRS core data to account for potential sample selection bias. Control variables include age, race, gender, education, asset holdings, and self-reported health status. The *lambda* coefficient in the Heckman models represents the inverse Mills ratio.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Regression Results of Online Insurance (Financial Literacy > 0.5)

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman
Cognitive Decline	-0.3371**	-0.5237***	-0.3860**	-0.4677***
	(0.1686)	(0.1876)	(0.1683)	(0.1735)
Cognitive Decline^2	0.3464	0.6796**	0.4480*	0.6111**
	(0.2350)	(0.2703)	(0.2316)	(0.2452)
lambda		-0.1078***		-0.0517**
		(0.0359)		(0.0244)
N	1066	2829	1066	2829
Demographic Control	No	No	Yes	Yes

Note: This table reports regression estimates of cognitive decline on online insurance usage among individuals with financial literacy above 0.5. The models include both linear and quadratic terms for cognitive decline to capture potential non-linear effects. Columns (1) and (3) report OLS estimates based on the LBQ sample, while columns (2) and (4) report results from Heckman selection models using HRS core data. Demographic control variables include age, race, gender, education, asset and self-reported health . The *lambda* coefficient in the Heckman models represents the inverse Mills ratio.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Regression Results of Online Insurance (Financial Literacy < 0.5)

	(1) OLS	(2) Heckman	(3) OLS	(4) Heckman
Cognitive Decline	-0.1179***	-0.0721**	-0.0418	-0.0120
	(0.0288)	(0.0320)	(0.0314)	(0.0332)
lambda		-0.0992***		-0.0640***
		(0.0251)		(0.0207)
N	1626	5825	1626	5825
Demographic Control	No	No	Yes	Yes

Note: This table reports regression estimates of cognitive decline on online insurance usage among individuals with financial literacy below 0.5. The models include only the linear term of cognitive decline. Columns (1) and (3) report OLS estimates based on the LBQ sample, while columns (2) and (4) report results from Heckman selection models using HRS core data. Demographic control variables include age, race, gender, education, asset and self-reported health . The *lambda* coefficient in the Heckman models represents the inverse Mills ratio.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Robustness Check

	(1) OLS	(2) Heckman	(3) Semiparametric
Cognitive Decline	-0.1444	-0.2993*	-0.1609
	(0.1705)	(0.1763)	(0.1029)
Cognitive Decline^2	0.0569	0.2959	0.0656
	(0.1890)	(0.1987)	(0.1196)
Online Banking	0.0119	0.0119	0.0160
	(0.0192)	(0.0191)	(0.0105)
Online Insurance	0.0458	0.0363	0.0277
	(0.0373)	(0.0371)	(0.0204)
Securing Fin. Future	-0.0707***	-0.0705***	-0.0566***
	(0.0237)	(0.0235)	(0.0131)
Control Fin. Situation	-0.0840***	-0.0845***	-0.0903***
	(0.0278)	(0.0276)	(0.0154)
Numeracy Test Score	0.0048	-0.0034	-0.0002
	(0.0078)	(0.0082)	(0.0043)
SSN	0.0003	-0.0008	-0.0019
	(0.0091)	(0.0091)	(0.0050)
Number of Children	0.0058*	0.0085***	0.0063***
	(0.0032)	(0.0033)	(0.0018)
Live with Partner	-0.0264**	-0.0457***	-0.0334***
	(0.0128)	(0.0137)	(0.0071)
lambda		-0.1266***	
		(0.0283)	
N	2692	8654	8654
Demographic Control	Yes	Yes	Yes

Note: This table reports robustness checks using three different estimation approaches: OLS (column 1), Heckman selection model (column 2), and a semiparametric estimator (column 3). The dependent variable is an indicator of fraud victimization. Cognitive decline and its squared term capture nonlinear effects. All specifications include fintech adoption (online banking and online insurance), financial literacy proxies (securing financial future, control of financial situation, numeracy test score), and guardianship proxies (SSN usage, number of children, and living with a partner), along with demographic controls (age, race, gender, education, assets, and self-reported health). The *lambda* coefficient in the Heckman model denotes the inverse Mills ratio. Standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Comparative statics

Impact of $\uparrow \delta$ on	Low Literacy Regime Phase I $(0 < \delta < 1)$	High Literacy Regime Phase I $(0 < \delta < \delta)$	 Phase II $(\delta^{<}\delta < \tilde{\delta})$	 Phase III $(\tilde{\delta} < \delta < 1)$
e^*	$\downarrow$	$\downarrow$	$\downarrow$	$\uparrow$
π	$\downarrow$	$\downarrow$	$\uparrow$	$\uparrow$
U_E	$\downarrow$	$\downarrow$	$\downarrow$	$\uparrow$
EU_F	Ambiguous	Ambiguous	$\uparrow$	$\uparrow$

Note: As proved in Theorem A.1, low Literacy regime means: $1 - 2\phi_1 \geq \phi_0 g(k, \delta_0)$. High Literacy regime means: $1 - 2\phi_1 < \phi_0 g(k, \delta_0)$ where $s = 1/(1 + e^{k(1-\delta_0)})$ and the generalized fraction term $g(k, \delta_0) = 2s - ks(1 - s)$. δ^* is the interior critical point where $d\pi/d\delta = 0$, occurring in $(0, \tilde{\delta})$. $\tilde{\delta}$ is the critical point where $de^*/d\delta = 0$ (minimum of e^*). #: The three phases of cognitive decline are I: Cognitive Burden, II: Vulnerability Amplification, III: Resilience Recovery (See main texts for detailed explanation).
Notations: δ is the degree of cognitive decline, e^* is the optimal fintech adoption level, π is the fraud success probability, UE is the elder's utility, EUF is F's expected utility (a proxy for probability of committing crime because F will commit a crime if $EUF > 0$).