Actual and Perceived Financial Knowledge over the Life Cycle *

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Abstract

What happens when households believe they know more than they actually do about financial matters? I address this question by combining causal evidence with a calibrated life-cycle model. First, using U.S. household survey data, I construct unjustified confidence as the residual from regressing perceived knowledge on actual financial knowledge and instrument it with parental financial education during childhood. Second, I embed biased beliefs about their own knowledge into a life-cycle portfolio choice model in which households learn slowly from noisy investment returns. Both approaches point to the same margin. The empirical estimates indicate that unjustified confidence raises early retirement-account withdrawals by 17 percentage points and increases mortgage distress and credit-card overuse; the calibrated model translates these patterns into a welfare cost of 1.72 percent of retirement consumption, with one household in ten losing more than 8 percent.

Keywords: financial literacy, overconfidence, perceived financial knowledge, household finance, life cycle model

JEL Codes: D14, D15, D91, G51, G53

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1 Introduction

Decades of financial literacy research have shown that higher measured financial knowledge correlates with better financial choices. But what happens when households believe they know more than they actually do?

In this paper, I address this question on two fronts. First, on the empirical side, I propose a novel strategy to identify the causal effect of overconfidence in financial knowledge on household behavior. I combine Parker and Stone (2014)'s unjustified confidence approach with an instrumental variable (IV) based on early-life parental financial education. I find that overconfidence leads households to make costly financial decisions, including drawing down retirement savings, falling behind on mortgages, and overusing credit cards.

Second, on the theoretical front, I develop a quantitative portfolio choice life cycle model in which households accumulate financial knowledge and form beliefs about it based on noisy return realizations, separating perceived from actual knowledge along the life cycle. I find that the welfare cost of these biased beliefs concentrates in retirement.

Beliefs about one's own financial knowledge matter because people act on what they believe they know (Kramer, 2016). Self-assessed knowledge predicts financial behavior at least as well as measured knowledge, and the two together predict it better still (Allgood and Walstad, 2016; Anderson, Baker, and Robinson, 2017). An inaccurate self-assessment of financial knowledge, whether overconfident or underconfident, can shift thresholds for borrowing, portfolio risk-taking, and demand for financial advice.

To measure actual financial knowledge (AFK), I use the number of correct responses to the "Big Three" questions[1], a score from 0 to 3 (Lusardi and Mitchell, 2007). I measure perceived financial knowledge (PFK) as respondents' self-assessed financial competence on a seven-point Likert scale. To compare the two, I follow Parker and Stone (2014) and construct unjustified confidence (UJC) as the residual from a regression of PFK on AFK. By construction, UJC is the component of perceived financial knowledge that measured knowledge does not explain.

Because unjustified confidence is likely correlated with unobservables that also affect financial behavior, I instrument it with an indicator for whether the respondent received financial education from a parent. Identification rests on an exclusion restriction: conditional on AFK and a rich set of controls, parental financial education affects outcomes only through unjustified confidence. In Section 5, I probe this restriction against alternative explanations and bound the consequences of its failure.

[1] A set of questions designed to capture basic financial knowledge about inflation, risk diversification, and compounding. See Appendix A for details.

Households whose unjustified confidence sits one standard deviation above the mean are roughly 17 percentage points more likely to draw on their retirement savings early. The effect is driven by households with low actual financial knowledge, who are most vulnerable to their own overconfidence. Unjustified confidence is also positively associated with mortgage distress and costly credit-card use. Actual financial knowledge, in contrast, is associated with fewer adverse outcomes.

Each of these estimates is a snapshot of one financial decision. The model traces how biased beliefs compound over the life cycle into a welfare cost. Households face uninsurable income risk over a finite horizon with working and retirement periods, and choose consumption, portfolios, and investment in financial knowledge. Perceived financial knowledge, formed by Bayesian updating, shapes their decisions.

I calibrate the model to moments from the NFCS, including the age profile of actual knowledge and the joint distribution of perceived and actual knowledge among the youngest households. I then compare this economy with a full-information benchmark, where households observe their true knowledge, and measure the welfare difference as a consumption-equivalent change in lifetime resources.

In the model, biased beliefs lead households to invest less in financial knowledge and take on more portfolio risk than they would under full information. The wedge pushes them toward smaller and more fragile retirement wealth. The welfare loss amounts to 1.72 percent of retirement consumption.

What households believe they know does not merely correlate with their choices. It causally shapes them, beyond what they actually know. In the calibrated model, these beliefs compound into a welfare cost that surfaces in retirement. The households most exposed are the ones least aware of it. This suggests financial literacy efforts should not only transmit knowledge but help households recognize what they do not know.

2 Related literature

Since the "Big Three" was introduced by Lusardi and Mitchell (2007), researchers have linked financial knowledge to a wide range[2] of financial outcomes (Lusardi and Mitchell, 2007; Calvet, Campbell, and Sodini, 2009; Van Rooij, Lusardi, and Alessie, 2011; Disney and Gathergood, 2013; Klapper, Lusardi, and Panos, 2013; Bianchi, 2016; Clark, Lusardi, and Mitchell, 2017; Gathergood and Weber, 2017). Yet, objective scores explain only part of household behavior, motivating a growing body of work that studies the subjective dimension

[2]For a review, see Lusardi and Mitchell (2023).

of financial knowledge.

This paper makes two contributions. First, I provide causal evidence on the effects of overconfidence on financial behavior. Second, I introduce actual and perceived financial knowledge into a standard quantitative life-cycle portfolio choice model. To place these contributions in context, I first review prior work on perceived financial knowledge and then summarize how financial knowledge and overconfidence are incorporated into theoretical models.

On the empirical side, the closest prior work documents correlations between overconfidence and financial behavior. Allgood and Walstad (2016) and Lee and Hanna (2020) both use the NFCS, linking categorical measures of overconfidence to credit-card use and to early retirement withdrawals and loans, some of the outcomes I study. Anderson, Baker, and Robinson (2017) go further on measurement, constructing each respondent's prior belief about their own knowledge, and find that perceived knowledge outpredicts actual knowledge. I build on this work in two ways: a continuous measure of overconfidence (Parker and Stone, 2014), and an instrumental-variables design that identifies its causal effect.

Households systematically overestimate their knowledge, and the least knowledgeable most of all (LaBorde, Mottner, and Whalley, 2013; Anderson, Baker, and Robinson, 2017). This gap carries into behavior: overconfident households make worse financial decisions (Balasubramnian and Sargent, 2020). Overconfidence also shapes behavior in financial markets, predicting riskier portfolios and higher participation (Barber and Odean, 2001; Xia, Wang, and Li, 2014; Chu et al., 2017), while investors who recognize their limits participate less (Bazley, Bonaparte, and Korniotis, 2021).

Although informative, much of this evidence is correlational. Confidence may respond to past financial outcomes through learning, and both confidence and behavior may reflect unobserved characteristics. The instrumental-variables design I introduce addresses both threats.

In a robustness exercise, I treat "don't know" responses as a confidence signal, to ensure the objective measure is not mechanically contaminated by confidence (Kim and Mountain, 2019). This draws on the gender-gap literature, where prior studies document that differences in self-assessed knowledge and "don't know" responses account for a substantial share of the gap (Bucher-Koenen, Lusardi, et al., 2017; Cupák et al., 2018; Aristei and Gallo, 2022; Bucher-Koenen, Alessie, et al., 2024).

Theoretical work on financial knowledge is scarcer, and most of it models knowledge as a form of human capital in life-cycle consumption-saving models. Jappelli and Padula (2013) introduce a multi-period consumption model in which consumers choose to invest in financial knowledge at a cost to increase returns on wealth, showing that financial knowledge and wealth co-move over the life cycle. Lusardi, Michaud, and Mitchell (2017) develop a dynamic stochastic intertemporal model with portfolio choice and depreciating, costly financial knowledge acquisition. In more recent work, Kim (2024) builds on this work and embeds knowledge accumulation in a heterogeneous-agent general equilibrium model.

A common feature of these contributions is that households fully observe their own financial knowledge and condition choices on the true stock. By contrast, models of overconfidence in the behavioral finance literature allow agents to misperceive ability or signal precision, generating distorted beliefs that drive retail trading (Odean, 1998; Gervais and Odean, 2001). Although these frameworks offer a useful template for modeling overconfidence, they abstract from life-cycle structure and endogenous knowledge accumulation.

Recent work provides microfoundations for biased learning and memory that can generate overconfidence. Gödker, Jiao, and Smeets (2025) document positive recall bias, with gains recalled more often than losses, generating overestimation of ability. Related work formalizes distortions from representativeness and associative memory (Bordalo, Coffman, Gennaioli, and Shleifer, 2016; Bordalo, Coffman, Gennaioli, Schwerter, et al., 2021; Enke, Schwerter, and Zimmermann, 2024) and from motivated beliefs and ego utility (Bénabou and Tirole, 2002; Brunnermeier and Parker, 2005; Köszegi, 2006; Zimmermann, 2020).

This paper connects these strands by introducing biased beliefs about financial knowledge into a quantitative life-cycle portfolio choice model disciplined by survey data. I build on the financial knowledge models of Jappelli and Padula (2013) and Lusardi, Michaud, and Mitchell (2017). In their frameworks, agents observe their knowledge stock directly. In mine, they observe only a subjective assessment, formed by Bayesian updating on noisy realized returns. The model is calibrated to match the age profile of actual knowledge, and the same structure generates a gap between perceived and actual knowledge over the life cycle. I now turn to the data and identification strategy that operationalize the empirical contribution; the model returns in Section 6.

3 Data and empirical strategy

3.1 The NFCS data

The primary data source is the National Financial Capability Study (NFCS), commissioned by the Financial Industry Regulatory Authority in collaboration with the U.S. Department of the Treasury. The NFCS is a repeated cross-sectional household survey, conducted every three years since 2009, that measures the financial capabilities of U.S. adults through an online survey of more than $25,000$ respondents across all states. Respondents are weighted to match the population demographics.

I use the 2015 NFCS wave because it is the only wave that elicits parental financial education, the instrument I introduce in Section 3.3; the analysis is therefore cross-sectional. After dropping observations with missing values, the sample contains 23,343 of 27,564 adults. Appendix A reports summary statistics for the final sample, including descriptive statistics for the knowledge measures and outcomes.

I draw two core indicators of financial knowledge from the NFCS. First, actual financial knowledge (AFK) is the number of correct responses to the "Big Three" questions of Lusardi and Mitchell (2007), a discrete score from 0 to 3. Second, perceived financial knowledge (PFK) is a measure of respondents' self-assessed financial competence, recorded on a seven-point Likert scale with higher values indicating greater perceived knowledge[3].

Across the sample, about 40% of respondents answered all three objective questions correctly, and about 10% answered none correctly. Among those who failed all three, over 40% nonetheless rated their perceived knowledge above the median. These patterns indicate a widespread gap between perceived and actual financial knowledge, especially overconfidence, consistent with prior evidence that households overestimate their financial competence (Gervais and Odean, 2001; Allgood and Walstad, 2016; Anderson, Baker, and Robinson, 2017).

Figure 1 shows how perceived and actual knowledge relate. Perceived knowledge rises with measured knowledge and its spread narrows at higher levels (Panel A): more knowledgeable individuals hold more precise beliefs about their own competence. Both measures rise with age (Panel B), but the gap shrinks at older ages, consistent with self-perception aligning with objective ability later in life.

3.2 Measuring overconfidence

The psychology literature identifies at least three distinct concepts of overconfidence: (i) overestimation of one's actual ability; (ii) overplacement of how one ranks relative to others; and (iii) overprecision or excessive certainty about one's beliefs (Moore and Healy, 2008). This paper follows most existing studies and adopts the first definition. Assessing it empirically requires measures of both perceived and actual knowledge, plus a metric to compare them.

In binary terms, respondents who score low on the objective questions but rate their knowledge as high are classified as overconfident, and vice versa. Researchers usually implement this classification with sample splits, labeling as overconfident those with below-average actual knowledge but above-average perceived knowledge.

[3] See Appendix A for the exact wording of both questions.

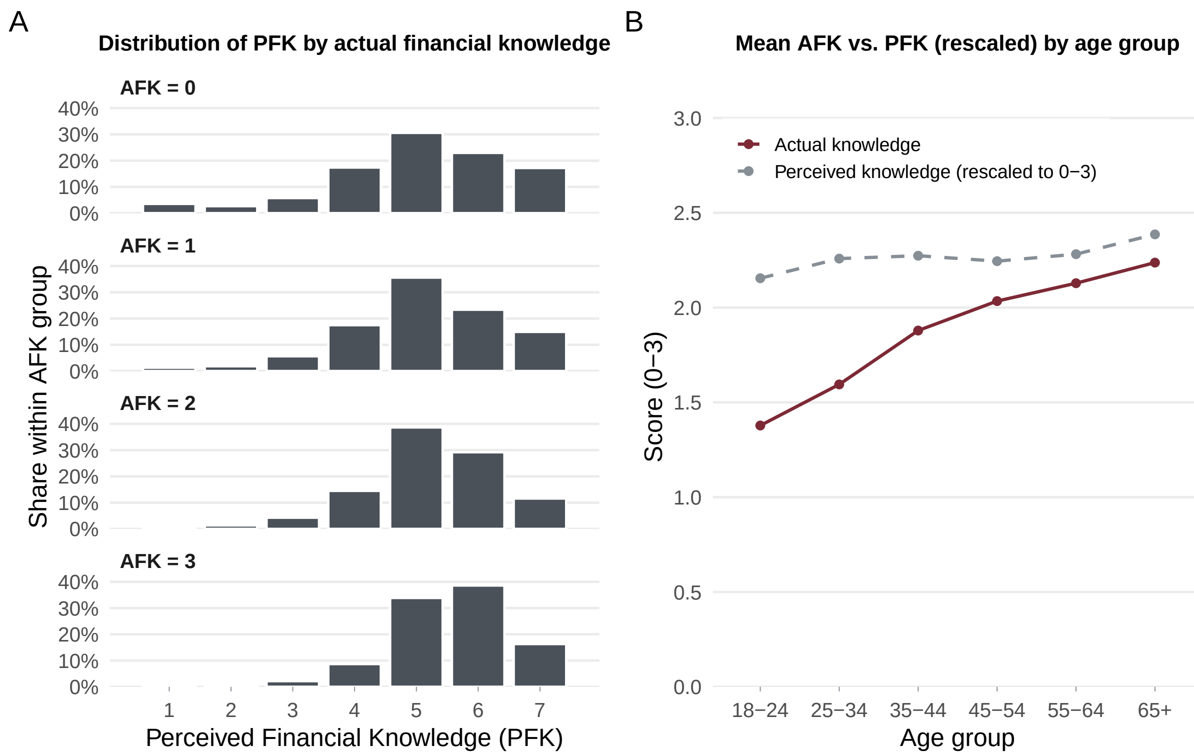

Figure 1: Panel A: PFK shifts right and tightens as AFK rises, but even respondents with AFK $= 0$ cluster at PFK ≥ 5. Panel B: AFK and PFK both rise with age, and the gap narrows because AFK rises faster. Source: NFCS 2015 analytic sample, $N = 23{,}343$ (same sample used in the regressions); means in Panel B use NFCS sampling weights.

This sample-split approach has shortcomings. Respondents classified as overconfident must, by construction, score below average, which restricts variation in actual knowledge within the group and conflates knowledge with confidence. The residual approach proposed by Parker and Stone (2014) solves this: regress PFK on AFK and take UJC as the estimated residual $\widehat{\varepsilon}_i$. By construction, UJC is orthogonal to AFK and continuous, which simplifies instrumental variable estimation.

$$\begin{aligned} \mathrm{PFK}_i &= \alpha + \beta \cdot \mathrm{AFK}_i + \varepsilon_i, \\ \mathrm{UJC}_i &\equiv \widehat{\varepsilon}_i. \end{aligned} \tag{1}$$

Table 1 reports the regression in Equation 1 under two specifications: column (1) treats AFK as continuous, imposing a constant marginal effect on PFK across knowledge levels; column (2) is saturated, with one indicator for each of the four AFK values.

Both specifications confirm that PFK rises monotonically with AFK. The saturated specification is more flexible and does not require the linearity assumption that the continuous specification imposes. I use the saturated specification's residual as UJC in the main analysis.[4]

	Continuous (1)	Saturated (2)
AFK	0.185***	
	(0.008)	
AFK = 1		0.075**
		(0.035)
AFK = 2		0.168***
		(0.033)
AFK = 3		0.500***
		(0.032)
Constant	4.96***	5.06***
	(0.019)	(0.030)
Observations	23,343	23,343
Adjusted R^2	0.03	0.03

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 1: UJC construction: continuous vs. saturated specifications for the PFK–AFK regression

A positive UJC marks an overconfident respondent, whose perceived knowledge exceeds the average for their AFK level; a negative value marks underconfidence. I standardize UJC within the analytic sample, so coefficients are reported per standard deviation, roughly a one-point shift on the 1–7 PFK scale. Because UJC is orthogonalized against AFK, which is measured with error, Section 5 reconstructs it from the Big Six and DK-adjusted knowledge measures.

3.3 Identification strategy

Identifying the causal effect of unjustified confidence requires addressing its endogeneity: UJC is likely correlated with unobserved traits, such as cognitive ability or optimism, that also affect financial behavior. Because perceived knowledge and the outcomes are measured together, financial distress could itself depress self-assessed knowledge. I address both concerns with an instrumental variable based on parental financial education, which predates adult life and is therefore unaffected by later financial behavior.

[4] The two residuals are highly correlated and the estimates are essentially unchanged under the continuous specification.

	AFK (1)	PFK (2)	UJC (3)
FinEdu from institutions	0.134***	0.296***	0.256***
	(0.014)	(0.015)	(0.016)
FinEdu from Parents	-0.006	0.238***	0.240***
	(0.012)	(0.013)	(0.014)
HH characteristics	Yes	Yes	Yes
Observations	23,343	23,343	23,343
Adjusted R^2	0.22	0.22	0.17

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Parental financial education and measures of actual financial knowledge, perceived financial knowledge, and unjustified confidence. Full specification in Appendix Table B1.

I instrument UJC with parental financial education, an indicator for whether a respondent's parents or guardians taught them about financial matters (exact wording in Appendix A). The exclusion restriction requires that parental financial education affect adult outcomes only through unjustified confidence, conditional on AFK and the controls.

The mechanism is timing: by adulthood, financial knowledge is shaped mostly by later education, work, and direct financial experience, so what parents taught in childhood is largely overwritten. Section 5 offers suggestive evidence consistent with this: parental financial education predicts AFK among the youngest respondents but not among older ones. Beliefs about that knowledge, in contrast, form early and update slowly, as documented in the literature on belief persistence (Bordalo, Coffman, Gennaioli, Schwerter, et al., 2021; Enke, Schwerter, and Zimmermann, 2024).

Table 2 reports regressions of AFK, PFK, and UJC on parental financial education with a full set of demographic and socioeconomic controls. Parental financial education strongly predicts perceived financial knowledge and UJC but not actual financial knowledge, whereas formal financial education (school or workplace) is significantly correlated with AFK. In adulthood, the parental financial teaching channel shifts perceived knowledge, not actual knowledge. Section 5 stress-tests the exclusion restriction with proxies for other parental channels and Conley bounds.

Under the exclusion restriction, the causal effect of UJC on financial behavior is identified by the following two-stage least squares system:

$$\begin{aligned} \text{First stage:} \quad & \text{UJC}_i = \alpha_0 + \alpha_1 \text{Parental.FinEdu}_i + \boldsymbol{\alpha}_2' \mathbf{X}_i + \nu_i, \\ \text{Second stage:} \quad & Y_i = \beta_0 + \beta_1 \widehat{\text{UJC}}_i + \boldsymbol{\beta}_2' \mathbf{X}_i + \varepsilon_i, \end{aligned} \tag{2}$$

where UJC_i is unjustified confidence, Y_i is the financial outcome of interest, $\mathrm{Parental.FinEdu}_i$ is a binary indicator for having received financial education from parents (the instrument), and $\widehat{\mathrm{UJC}}_i$ is the first-stage fitted value.

The vector $\mathbf{X}_i$ includes actual financial knowledge (AFK_i), demographics (age group, gender, ethnicity, marital status, state of residence, dependent children), socioeconomic indicators (education, employment, income, home ownership, debt position, liquidity constraints, prior formal financial-education exposure), and risk aversion. The parameter of interest is β_1, the causal effect of unjustified confidence on Y_i.

Table 3 reports the first stage on the analytic sample: parental financial education raises UJC by 0.21 standard deviations conditional on actual knowledge and the full control vector, with an F-statistic of 303, well above conventional thresholds (Stock and Yogo, 2005). The instrument remains strong under the Olea-Pflueger effective F (Montiel Olea and Pflueger, 2013), and the headline estimates are robust to weak-instrument-robust Anderson-Rubin inference (Anderson and Rubin, 1949), state-clustered standard errors, and multiple-hypothesis corrections (Appendix Table B8). The 2SLS coefficient identifies a local average treatment effect (LATE) on the resulting compliers.

	UJC (1)
Parental.FinEdu	0.211***
	(0.012)
F-stat (IV)	303.2
Observations	23,343
Adjusted R^2	0.19

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: First-stage regression of UJC on Parental.FinEdu, full analytic sample. All controls included.

4 Results

This section reports the 2SLS estimates of Equation 2. The headline outcome is retirement-account leakage; mortgage distress and credit-card overuse follow. All coefficients on UJC are reported per standard deviation, and heteroskedasticity-robust standard errors are in parentheses.

4.1 Overconfidence and retirement-account leakage

About 56 percent of the sample owns a defined-contribution (DC) retirement account. These accounts permit two ways to draw on the balance before retirement: a plan loan and a hardship withdrawal.

Financial literacy correlates with sound retirement decisions, but the perceived component does most of the predictive work (Anderson, Baker, and Robinson, 2017). While recent work emphasizes temptation as a behavioral channel (Andersen et al., 2026), I document a distinct one: overconfidence. Households may overestimate their ability to repay the loan or rebuild the account, taking on more risk and drawing down retirement savings.

	Retirement loan			Retirement withdrawal		
	Pooled (1)	AFK $\leq$ 1 (2)	AFK $\geq$ 2 (3)	Pooled (4)	AFK $\leq$ 1 (5)	AFK $\geq$ 2 (6)
UJC	0.167***	0.414***	-0.008	0.166***	0.351***	-0.007
	(0.034)	(0.089)	(0.039)	(0.030)	(0.077)	(0.031)
AFK	-0.033***	-0.047**	-0.026**	-0.036***	-0.052***	-0.025***
	(0.007)	(0.023)	(0.010)	(0.006)	(0.020)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,002	2,804	10,198	13,002	2,804	10,198
Adjusted R^2	0.15	0.27	0.05	0.19	0.34	0.05
F-test (1st stage), UJC	118.3	38.5	62.3	118.3	38.5	62.3

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: IV estimates of the effect of UJC on retirement-account leakage, pooled and by AFK subsample. The effect concentrates in the low-knowledge group; the heterogeneity is driven by the reduced form, not by first-stage scaling (Appendix Table B3).

Unjustified confidence raises retirement leakage substantially. Table 4 reports IV estimates for the loan (columns 1–3) and hardship-withdrawal (columns 4–6) outcomes, each in the pooled subsample and split at AFK ≤ 1 and AFK ≥ 2. In the pooled sample, a one-standard-deviation increase in UJC raises the probability of both outcomes by roughly 17 percentage points, large relative to the sample-mean leakage rate of around 9 percent.

The split columns (2–3 and 5–6) indicate that the pooled effect is concentrated in the low-knowledge group: among low-AFK respondents, a one-standard-deviation increase in UJC raises the loan probability by 41.4 percentage points and the hardship-withdrawal probability by 35.1 percentage points, more than double the full-sample estimates, while for high-AFK respondents both coefficients are statistically null. Actual financial knowledge enters negatively throughout, and the instrument is strong in every column, with first-stage F well above the conventional threshold of 10. The cost of overconfidence falls hardest on the households least equipped to bear it.

The same concentration appears among self-directors of defined-contribution plans, where UJC raises both outcomes by about 22 percentage points, while the effect is null among those whose plan is managed by others. It is also about three times larger among men than among women (Appendix Table B2, Panels A and C).

These splits point to a common channel: unjustified confidence becomes costly only when households have scope to act on it. That scope is institutional for self-directors and behavioral for men, consistent with the gender-overconfidence literature (Bucher-Koenen, Alessie, et al., 2024). Formal financial education changes neither, and does not moderate the effect (Appendix Table B6).

4.2 Overconfidence: mortgage distress and credit-card overuse

Tapping retirement savings often signals a liquidity need, and a household confident in its ability to repay or rebuild is more likely to act on that need. The same belief should extend to other corners of household finance. I examine two: mortgages, a major component of household balance sheets, and credit cards, a common short-term liquidity channel.

	Underwater Mortgage (1)	Late Mortgage (2)
UJC	0.109***	0.145**
	(0.040)	(0.061)
AFK	-0.052***	-0.060***
	(0.008)	(0.013)
Controls	Yes	Yes
Observations	8,458	8,458
R^2	0.18	0.20
F-test (1st stage), UJC	102.39	102.39

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: IV estimates of the effect of UJC on mortgage outcomes

Unjustified confidence raises mortgage distress. Table 5 reports the IV estimates on the mortgage subsample for two outcomes, controlling for the year of home purchase: being underwater on the mortgage (column 1) and the frequency of late mortgage payments on a 0–2 scale (column 2). A one-standard-deviation increase in UJC raises the underwater probability by 10.9 percentage points and the late-payment frequency by 0.15 points.

Credit-card behavior tracks the same channel at shorter horizons. Table 6 reports IV estimates on the credit-card subsample for taking a cash advance (column 1) and exceeding the credit limit (column 2). A one-standard-deviation increase in UJC raises the probability of a cash advance by 5.0 percentage points and of exceeding the credit limit by 7.3 percentage points.[5]

	Took a cash advance (1)	Exceeded credit limit (2)
UJC	0.050**	0.073***
	(0.022)	(0.019)
AFK	-0.034***	-0.027***
	(0.004)	(0.003)
Controls	Yes	Yes
Observations	19,287	19,287
R^2	0.10	0.13
Wald (1st stage), UJC	218.01	218.01

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: IV estimates of the effect of UJC on credit-card behaviors

Ordinary least squares understates these effects throughout. Appendix Table B4 reports OLS, reduced-form, and 2SLS estimates side by side for all six outcomes; the 2SLS coefficients are several times larger than the OLS coefficients. Two forces push in this direction: classical measurement error in self-assessed knowledge attenuates the OLS association toward zero, and 2SLS identifies a local effect for compliers rather than a population average, weighted toward the low-knowledge households where the effect is largest (Table 4).

Under the exclusion restriction maintained in Section 3.3, these 2SLS estimates identify a causal effect of unjustified confidence on household financial behavior across a range of decisions: retirement-account leakage, mortgage distress, and credit-card overuse. The effect concentrates where households can act on their beliefs, particularly among low-knowledge respondents and those who direct their own retirement-plan investments, and is not blunted by formal financial training.

These estimates capture the behavioral channel at a single point in time. A household that mistakes its own competence today is the same household that compounds the mistake across the life cycle. Section 5 probes the IV estimates against threats to the exclusion

[5] Appendix B repeats the AFK and formal financial-education splits for the mortgage and credit-card outcomes, with the same pattern.

restriction and alternative specifications. The model in Section 6 then embeds biased beliefs into a life-cycle portfolio-choice problem and translates the cross-sectional estimates here into a welfare cost.

5 Robustness Analysis

This section probes the robustness of the retirement-leakage estimates along three dimensions: (i) alternative constructions of UJC, (ii) a direct-assistance channel from parents, and (iii) plausibly exogenous bounds on the exclusion restriction. The same checks for the mortgage and credit-card outcomes are reported in the appendix.

5.1 Alternative specifications

I re-define UJC using two alternative knowledge measures while keeping the estimation approach and control set identical to Section 3.3. First, I swap the baseline AFK (the Big Three) for an expanded Big Six that adds questions on loan interest, mortgage amortization, and bond pricing.

Second, following Bucher-Koenen, Alessie, et al. (2024), I account for "don't know" (DK) responses on the Big Three by adding the respondent's DK count when constructing UJC. If choosing "don't know" reflects low confidence rather than a genuine knowledge gap, the objective measure is mechanically depressed for low-confidence respondents, contaminating UJC. Conditioning on the DK count blocks that channel.

I apply these alternative specifications to both retirement outcomes: loan and hardship withdrawal.

In addition to these tests, I augment the main IV specification with two proxies for ongoing parental involvement: an indicator for respondents who received income transfers from relatives in the previous 12 months, and an indicator for co-residence with parents. These variables capture direct involvement by parents that affects outcomes outside the confidence and actual-knowledge channels.

Parents who emphasize financial education are also more likely to provide direct assistance or ongoing guidance later in life, opening a pathway plausibly distinct from confidence or actual knowledge. I include both proxies in the first stage and in the second stage; this appears as column (4).

Column (4) checks whether the UJC estimate survives once a plausible direct-assistance channel is absorbed. For both retirement outcomes the coefficient attenuates by about 15 percent but remains positive and significant at the 1 percent level. Because the proxies themselves correlate with confidence and are not driven exclusively by parental financial education, the test is informative but not definitive.

Parental education could also shift time preference, since more patient households borrow less and save more for retirement. Regressing planning horizon on Parental.FinEdu yields a null effect. The instrument does not predict patience, so patience cannot be the omitted channel.

Tables 7 and 8 report the body specifications for the retirement loan and hardship-withdrawal outcomes. The coefficient on UJC remains positive and significant at the 1 percent level under both the Big Six and DK-adjusted constructions, and the relatives-involvement column attenuates it by about 15 percent, but the result survives.

Appendix Table B7 runs the same battery on the four non-retirement outcomes. The baseline, Big Six, and DK-adjusted columns deliver positive and significant coefficients on all four outcomes. The relatives-involvement column attenuates the coefficients more substantially; the result remains significant for underwater mortgages and credit-card over-limit fees, while late mortgages and cash advances lose significance at conventional levels.

As a final check, multiple-hypothesis-testing corrections leave all six headline outcomes significant at the 5 percent level (Appendix Table B8). Romano-Wolf p-values for retirement-loan and hardship-withdrawal remain below 0.001.

	Retirement account loan			
	Baseline	Big Six AFK	DK-adjusted	Relatives involvement
	(1)	(2)	(3)	(4)
UJC	0.167***	0.154***	0.168***	0.141***
	(0.034)	(0.030)	(0.036)	(0.034)
AFK	-0.033***	-0.019***	-0.049***	-0.034***
	(0.007)	(0.003)	(0.005)	(0.007)
Transfers from relatives				0.094***
				(0.010)
Lives with parents				0.008
				(0.021)
Controls	Yes	Yes	Yes	Yes
Observations	13,002	13,002	13,002	13,002
Wald (1st stage), UJC	118.26	122.74	86.69	113.49

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Alternative specifications: retirement-account loan

	Retirement account withdrawal			
	Baseline	Big Six AFK	DK-adjusted	Relatives involvement
	(1)	(2)	(3)	(4)
UJC	0.166***	0.154***	0.168***	0.139***
	(0.030)	(0.026)	(0.032)	(0.029)
AFK	-0.036***	-0.021***	-0.052***	-0.038***
	(0.006)	(0.002)	(0.004)	(0.006)
Transfers from relatives				0.100***
				(0.009)
Lives with parents				0.009
				(0.020)
Controls	Yes	Yes	Yes	Yes
Observations	13,002	13,002	13,002	13,002
Wald (1st stage), UJC	118.26	122.74	86.69	113.49

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Alternative specifications: retirement-account withdrawal

5.2 Parental financial education, confidence, and the exclusion restriction

The exclusion restriction requires that parental financial education affect outcomes only through UJC once AFK and the control set are held fixed. Column (1) of Table 2 shows that, conditional on household characteristics, parental financial education has little correlation with AFK. Respondents who report having learned from their parents display substantially higher perceived financial knowledge and higher UJC.

Figure 2 sharpens this pattern by age. For each outcome $Y \in \{\text{AFK, PFK, UJC}\}$, I estimate

$$Y_i = \alpha + \beta\,\text{Parental.FinEdu}_i + \boldsymbol{\delta}'\,\text{Age}_i + \boldsymbol{\theta}'\big(\text{Parental.FinEdu}_i \times \text{Age}_i\big) + \mathbf{C}_i'\kappa + \varepsilon_i \qquad (3)$$

and report β for ages 18–24 and $\beta + \theta_g$ for each other age group g, with 95 percent confidence intervals. The AFK gap is positive and statistically different from zero only for the youngest group, and null thereafter. PFK and UJC gaps are positive and significant in every age bin, highest among the young and stable across the life cycle. Actual knowledge acquired from parents fades; perceived knowledge and confidence persist.

With cross-sectional data I cannot separate age effects from cohort effects. The share reporting parental financial education ranges from 44 to 56 percent across cohorts, so the comparison is roughly balanced.

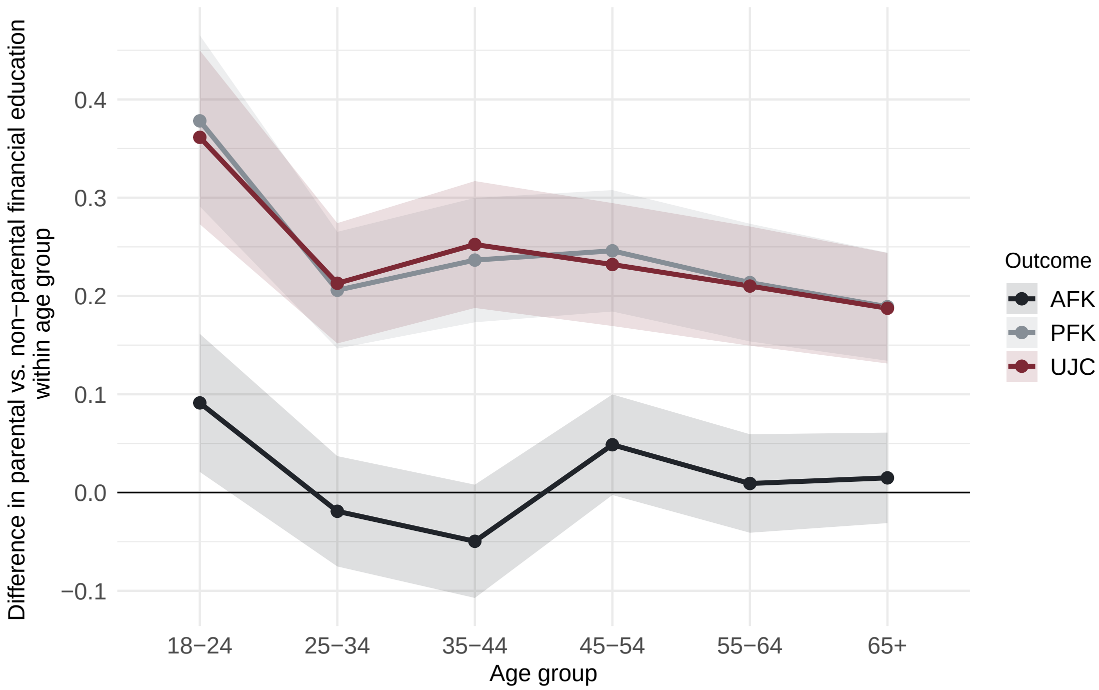

Figure 2: Difference in actual financial knowledge (AFK), perceived financial knowledge (PFK), and unjustified confidence (UJC) between respondents with and without parental financial education, by age group.

A residual concern is that parental financial education proxies for unobserved family background. In the 2018 and 2021 NFCS waves, where parents' education level is reported, observed parental education predicts AFK strongly but is uncorrelated with PFK and UJC, locating the channel through actual knowledge, which is controlled for in the second stage. The 2018 and 2021 waves lack the parental-teaching question used as the instrument, so this test is supplementary.

To quantify how sensitive the IV estimates are to small violations of the exclusion restriction, I implement the plausibly exogenous approach of Conley, Hansen, and Rossi (2012): I locally relax the exclusion restriction by allowing a limited direct influence of the instrument on the outcome, and estimate

$$\begin{aligned} \text{First stage:} \quad \text{UJC}_i &= \alpha_0 + \alpha_1 \, \text{Parental.FinEdu}_i + \boldsymbol{\alpha}_2' \mathbf{X}_i + \nu_i, \\ \text{Second stage:} \quad Y_i &= \beta_0 + \beta_1 \, \widehat{\text{UJC}}_i + \gamma \, \text{Parental.FinEdu}_i + \boldsymbol{\beta}_2' \mathbf{X}_i + \varepsilon_i, \end{aligned} \tag{4}$$

where $|\gamma| \leq \bar{\gamma}$ bounds the allowable direct effect of Parental.FinEdu_i on Y_i. I compute 2SLS estimates for a grid of $\gamma \in [-\bar{\gamma}, \bar{\gamma}]$ and report the range of β_1 values consistent with each case. I apply this to four outcomes: retirement loan, retirement hardship withdrawal, underwater mortgage, and credit-card cash advance. Figure 3 displays the confidence bounds for β_1

under allowable direct effects $\gamma \in [-0.05, 0.05]$. Figure C1 in the appendix reports the same exercise for the remaining mortgage distress and credit-card overuse outcomes.

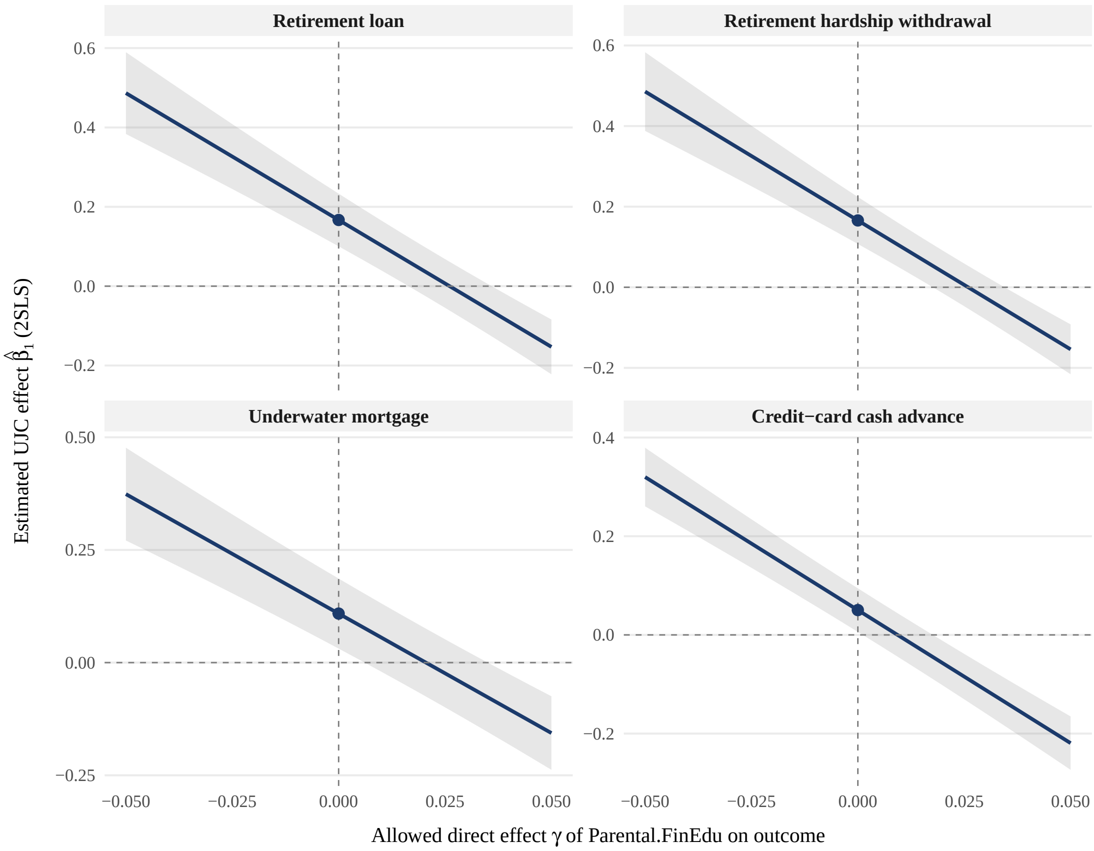

Figure 3: Conley plausibly exogenous bounds for the coefficient on unjustified confidence. Each panel shows 2SLS point estimates and 95% confidence intervals for $\widehat{\beta}_{UJC}$ as a function of the allowed direct effect γ of parental financial education on the outcome, for four outcomes: retirement loan, retirement hardship withdrawal, underwater mortgage, and credit-card cash advance.

As the allowable direct effect γ moves from zero toward small positive values, the 2SLS point estimates and confidence sets for all four outcomes drift toward zero. The lower 95 percent band first touches zero at $\gamma \approx 0.020$ for both retirement outcomes, $\gamma \approx 0.010$ for underwater mortgage, and $\gamma \approx 0.005$ for credit-card cash advance.

Interpreting these crossings requires taking a stand on the sign of γ. Economic reasoning suggests γ is unlikely to be positive for these outcomes: if parents who teach about finances also directly help in ways not fully captured by controls, that help should reduce distress, implying a negative correlation between the instrument and adverse outcomes. As a benchmark for the plausible magnitude of γ, adding the relatives-involvement proxies to the reduced-form regression of retirement leakage on Parental.FinEdu lowers the instrument coefficient by about 0.005, four times smaller than the γ at which the retirement coefficient loses significance.

The same sign prediction extends to other latent traits plausibly fostered by financially involved parents, which would also lower the incidence of all four adverse outcomes. Under $\gamma \leq 0$, the Conley exercise implies that the 2SLS coefficients are conservative and would strengthen, not vanish, if any remaining channel were removed.

6 The Model

To evaluate the welfare cost of overconfidence, I embed biased beliefs about financial knowledge into a finite-horizon, partial-equilibrium life-cycle model with consumption, portfolio choice, and endogenous investment in financial knowledge.

Financial knowledge raises the expected return on risky assets, but agents do not observe their own knowledge directly. They form and update beliefs about it from realized investment returns. The learning process allows perceived knowledge to diverge from actual knowledge and sustains a persistent wedge between perceived and actual knowledge in both directions across the life cycle. Agents enter the model at age 25, work until 65, receive a fixed pension from 66 onward, and face rising mortality risk; the model terminates at age 100.

6.1 Consumer's preferences and labor income process

The economy has a single non-durable consumption good. The agent chooses consumption c_t to maximize expected discounted lifetime utility. Preferences are time separable with constant relative risk aversion (CRRA). Period utility is

$$u(c_t) = \frac{c_t^{1-\gamma}}{1-\gamma}, \tag{5}$$

where γ is the coefficient of relative risk aversion. Lifetime utility satisfies the recursive formulation

$$U_t = u(c_t) + \beta\, \pi_{t+1}\, \mathbb{E}_t[U_{t+1}]\,, \tag{6}$$

where β is the subjective discount factor and π_{t+1} is the one-year survival probability. Following Cocco, Gomes, and Maenhout (2005), log labor income has a deterministic component $g(t)$, modeled as a cubic polynomial in age to capture the hump-shaped earnings profile, and a stochastic component that is the sum of a permanent random-walk innovation and a transitory shock:

$$
\begin{aligned}
\ln y_t &= g(t) + \mu_t + \eta_t, \\
\mu_t &= \mu_{t-1} + \varepsilon_t, \\
\varepsilon_t &\sim \mathcal{N}(0, \sigma_\varepsilon^2), \quad \eta_t \sim \mathcal{N}(0, \sigma_\eta^2).
\end{aligned}
\tag{7}
$$

Here μ_t is the permanent component and η_t the transitory component. Agents work until age 65; from age 66 onward, the income process is replaced by a fixed pension benefit y_{ret}.

6.2 Asset and financial knowledge accumulation

Earnings fluctuations are uninsurable, so the consumer accumulates precautionary savings to smooth consumption. Savings are allocated between two assets: a risk-free asset with gross return R^f, and a risky asset with stochastic gross return R^s_{t+1}.

The risky return depends on the consumer's financial knowledge f_t. Each period, the consumer chooses the share of savings allocated to the risky asset, $\alpha_t \in [0, 1]$, after paying a fixed per-period participation cost c_p whenever $\alpha_t > 0$.

To model the accumulation of financial knowledge over the life cycle, I follow Lusardi, Michaud, and Mitchell (2017) and Kim (2024) and augment an otherwise standard life-cycle portfolio choice model with endogenous investment in financial knowledge. Knowledge raises the expected return on the risky asset. Agents enter at age $t_0 = 25$ with an initial stock of knowledge f_0 and, each period, can invest $i_t \geq 0$ to increase it. Knowledge depreciates over time according to

$$
f_{t+1} = (1 - \delta_t)\, f_t + i_t, \tag{8}
$$

where $f_t \in [0, f_{\max}]$, with $f_{\max} = 100$, is the actual stock of financial knowledge in period t, δ_t is the age-dependent depreciation rate given by equation (9), and i_t is the investment in financial knowledge. This investment captures the acquisition of knowledge through financial education or financial advice. The cost of i_t is convex:

$$
\Pi(i_t) = \lambda\, i_t^{\omega}, \qquad \lambda > 0,\ \omega > 1,
$$

with increasing marginal cost in the quantity of knowledge acquired each period.

To capture the natural decline in memory and cognitive ability with age, I allow the depreciation rate δ_t in equation (8) to be age dependent rather than constant. At the entry age t_0, agents face no depreciation, $\delta_{t_0} = 0$, and the depreciation rate then rises convexly with age according to

$$
\delta_t = \delta_{\max}\Big(1 - \exp\big(-k\,(t - t_0)^{\kappa}\big)\Big), \tag{9}
$$

where $\delta_{\max}$ is the asymptotic depreciation rate, $\kappa > 1$ is a shape parameter governing the curvature of the age profile, and k scales how quickly the depreciation rate rises with age. Following Finke, Howe, and Huston (2017), who document a decline in financial literacy scores of about one percentage point per year after age 60, I anchor the depreciation rate at $\delta_t = 0.02$ at age 60. On the model's 0–100 knowledge scale, this corresponds to an absolute decline of one unit per year at the knowledge grid midpoint, broadly consistent with that evidence. Given $\delta_{\max} = 0.04$, the anchor equals $\delta_{\max}/2$ and pins $k = \ln 2/35^{\kappa}$. The parameters $\delta_{\max}$ and κ are calibrated jointly with the cost-function parameters to match the age profile of actual financial knowledge in the NFCS (Section 6.5).

The risky gross return increases monotonically with financial knowledge. Let $\phi_t \equiv f_t/f_{\max} \in [0,1]$ denote normalized knowledge. The risky return is then

$$R^s_{t+1} = R_\ell + \phi_t\,(R_h - R_\ell) + \sigma_R\,\zeta_{t+1}, \qquad \zeta_{t+1} \sim \mathcal{N}(0,1), \tag{10}$$

where $R_\ell < R_h$ are the gross expected returns at minimum and maximum knowledge, and $\sigma_R > 0$ is the standard deviation of the return innovation. The gross risk-free return is R^f. Given a risky share $\alpha_t \in [0,1]$, the portfolio gross return is

$$R_{t+1}(\alpha_t, f_t) = \alpha_t\,R^s_{t+1} + (1-\alpha_t)\,R^f. \tag{11}$$

Portfolio and knowledge choices condition on perceived knowledge f^P_t, but realized returns and the evolution of the true stock f_t depend on the unobserved actual knowledge.

6.3 Household's optimization problem

The household's problem is recursive. In each period t, the household observes cash-on-hand $x_t = a_t + y_t$, where a_t is beginning-of-period financial assets and y_t is current income, and perceived knowledge f^P_t, having drawn income innovations and realized last period's risky return. Following Gomes (2020), all wealth variables are normalized by permanent labor income so that the state space is stationary.

Because true knowledge f_t is unobserved, decisions condition on f^P_t. The household chooses c_t, α_t, and i_t to maximize expected lifetime utility subject to the budget constraint, the knowledge accumulation equation, the return process, and a no-borrowing constraint:

$$
\begin{aligned}
V(x_t, f_t^P) = \max_{c_t,\alpha_t,i_t}\; & u(c_t) + \beta\,\pi_{t+1}\,\mathbb{E}_t\big[V(x_{t+1}, f_{t+1}^P)\big]\,, \\
a_{t+1} &= [a_t + y_t - c_t - \Pi(i_t) - c_p\,\mathbf{1}\{\alpha_t > 0\}]\;R_{t+1}(\alpha_t, f_t), \\
f_{t+1} &= (1-\delta_t)\,f_t + i_t, \\
f_{t+1}^P &= \mathcal{B}\big(\Phi_t^*,\,R_{t+1}^s;\,i_t,\delta_t\big)\,, \\
\alpha_t &\in [0,1], \qquad a_{t+1} \geq 0.
\end{aligned}
\tag{12}
$$

The expectation in V integrates over the income shocks $(\varepsilon_{t+1}, \eta_{t+1})$ and the return innovation ζ_{t+1} using $5 \times 5 \times 5$ Gauss-Hermite quadrature during the working life. In retirement, when income is replaced by the fixed pension, the expectation is taken over the return innovation alone. The belief operator $\mathcal{B}$ updates the prior distribution Φ_t^* over knowledge levels into a posterior using realized returns, then propagates it forward by the chosen investment i_t and depreciation δ_t; the perceived stock f_{t+1}^P is the posterior mean. Section 6.4 gives the full update.

The model has no closed-form solution and is solved by backward induction on discrete grids: 41 log-spaced points for cash-on-hand, 21 points for the portfolio share $\alpha_t \in [0,1]$, and 16 points for financial knowledge. Off-grid policies are obtained by linear interpolation.

6.4 Belief updating and perceived financial knowledge

Survey evidence shows that individuals are often unsure of their own level of financial knowledge. In the model, agents cannot observe their true stock f_t directly. Instead, agents observe R_t, the portfolio return of equation (11) realized over the previous period. Because the share α_{t-1} and the risk-free rate R^f are known, the agent can recover the risky-asset return R_t^s from the identity $R_t = \alpha_{t-1}\,R_t^s + (1-\alpha_{t-1})\,R^f$, and uses it as a signal of their knowledge. Because returns are subject to idiosyncratic shocks, R_t^s is an imperfect signal of f_t, so perceived knowledge can diverge from actual knowledge. When $\alpha_{t-1} = 0$, the identity does not pin down R_t^s; no signal is observed and the posterior equals the prior on the propagated grid.

Let $\Phi_t^*(f)$ denote the agent's prior belief distribution over possible knowledge levels $f \in \mathcal{F}$ at the beginning of period t, before observing the return R_t^s, where $\mathcal{F}$ is a finite grid in $[0, f_{\max}]$. Given the prior and the observed return, beliefs are updated using Bayes' rule:

$$
\Phi_t(f) = \frac{p(R_t^s \mid f)\,\Phi_t^*(f)}{\sum_{f' \in \mathcal{F}} p(R_t^s \mid f')\,\Phi_t^*(f')},
\tag{13}
$$

where $p(R_t^s \mid f)$ is the likelihood of observing return R_t^s conditional on knowledge level f:

$$p(R_t^s \mid f) = \frac{1}{\sqrt{2\pi}\,\sigma_R} \exp\left(-\frac{(R_t^s - \bar{R}(f))^2}{2\sigma_R^2} \right), \tag{14}$$

with $\bar{R}(f) = R_\ell + (f/f_{\max})(R_h - R_\ell)$ the expected gross risky return at knowledge level f, and σ_R the standard deviation of the return innovation.

The agent's perceived knowledge f_t^P is the posterior mean,

$$f_t^P = \sum_{f \in \mathcal{F}} f\, \Phi_t(f), \tag{15}$$

and enters the state space as the basis for the consumption, portfolio, and knowledge-investment decisions in period t. The posterior is then carried into the next period as a prior, shifted by the agent's chosen investment i_t and the age-specific depreciation δ_t, so that the belief grid in $t+1$ reflects the law of motion of the true stock. This propagation applies the accumulation map of equation (8) to the posterior Φ_t, yielding the next-period prior Φ_{t+1}^*; the operator $\mathcal{B}$ in equation (12) composes it with the Bayesian update of equation (13). Realized risky returns continue to be driven by the unobserved actual knowledge f_t.

6.5 Model calibration and fit

This section describes how the model is simulated and calibrated, and how its fit is assessed. The calibration proceeds in two steps. First, I fix the preference, income, and return parameters and calibrate the cost and depreciation parameters of financial knowledge to match the age profile of actual financial knowledge in the NFCS. Second, I document the model's performance on untargeted moments, in particular perceived financial knowledge.

For any candidate parameter vector, I solve the Bellman equation by backward induction on the grids described in Section 6 and simulate 10,000 independent life cycles using common income and return shocks. Each household enters with zero financial wealth and a draw (f_{25}, f_{25}^P) from the empirical joint distribution of actual and perceived financial knowledge in the youngest NFCS age group (18–24).

In practice, I first draw an AFK category $F \in \{0, 1, 2, 3\}$ and a PFK category $M \in \{1, \dots, 7\}$ using the empirical joint frequency matrix $\mathcal{J}$, then draw continuous values for f_{25} and f_{25}^P uniformly within the corresponding score bins. This reproduces the cross-sectional dispersion and correlation between actual and perceived knowledge at the beginning of the life cycle, and implies that some agents start working life already overconfident or underconfident, consistent with the data. All model moments used in the calibration are computed from the simulated life-cycle output.

6.5.1 Parameter choices

Table 9 summarizes the parameter values used in the baseline calibration. The coefficient of relative risk aversion is set to $\gamma = 4$, following Lusardi, Michaud, and Mitchell (2017). The subjective discount factor is $\beta = 0.97$, following Gomes (2020). Survival probabilities $\{\pi_t\}$, the labor income process, the deterministic age profile $g(t)$, and the retirement benefit level y_{ret} are also taken from Gomes (2020).

The gross risk-free return is $R^f = 1.02$, and the risky return parameters in equation (10) are chosen so that the equity premium is $R_h - R_\ell = 0.04$ and the return innovation standard deviation is $\sigma_R = 0.16$, consistent with Campbell and Viceira (2002). The remaining parameters are calibrated internally to match the age profile of actual financial knowledge in the NFCS. They include the participation cost c_p, the depreciation parameters $(\delta_{\max}, \kappa)$, and the knowledge-cost parameters (λ, ω). Their values are reported in Table 9.

The calibration targets are the mean levels of actual financial knowledge (AFK) by age group in the NFCS. Let $A\bar{F}K_b^{\text{data}}$ denote the average AFK in age bin b in the data, and $A\bar{F}K_b^{\text{model}}$ the corresponding model moment. I focus on four working-age bins,

$$\mathcal{A} = \{25\text{–}34,\ 35\text{–}44,\ 45\text{–}54,\ 55\text{–}64\},$$

and choose the internal parameters to minimize the sum of squared deviations between model and data AFK means:

$$\mathcal{L} = \sum_{b \in \mathcal{A}} \left(A\bar{F}K_b^{\text{model}} - A\bar{F}K_b^{\text{data}} \right)^2. \tag{16}$$

The treatment of the 65+ age bin requires a modeling choice. In the NFCS, all respondents aged 65 and above are pooled into a single category that spans a wide segment of the life cycle. Imposing a single AFK target for this group would mechanically tie late-life knowledge to the behavior of the youngest retirees and could distort the fit for the working-age bins. For this reason, I exclude the 65+ AFK mean from the calibration set.

Figure 4 compares the model-implied age profile of actual financial knowledge to its empirical counterpart from the NFCS. The model tracks the average AFK in each working-age bin closely, reproducing both the level and the gradual rise in knowledge from ages 25 to 64.

Parameter	Value	Source
Preferences		
Risk aversion, γ	4.0	Lusardi, Michaud, and Mitchell (2017)
Discount factor, β	0.97	Gomes (2020)
Survival probabilities, $\{\pi_t\}$	-	Gomes (2020)
Income process		
Permanent shock SD, σ_ε	0.10	Gomes (2020)
Transitory shock SD, σ_u	0.10	Gomes (2020)
Deterministic profile, $g(t)$	-	Gomes (2020)
Retirement benefit, y_{ret}	0.68	Gomes (2020)
Returns and portfolio		
Risk-free gross return, R^f	1.02	Campbell and Viceira (2002)
Return innovation SD, σ_R	0.16	Campbell and Viceira (2002)
Equity premium, $R_h - R_\ell$	0.04	Campbell and Viceira (2002)
Participation cost, c_p	0.0025	Calibrated
Knowledge technology and costs		
Joint initial (f_{25}, f_{25}^P) distribution, $\mathcal{J}$	-	NFCS
Asymptotic depreciation rate, $\delta_{\max}$	0.04	Calibrated
Depreciation anchor, k	$\ln 2/35^\kappa$	Finke, Howe, and Huston (2017)
Depreciation shape, κ	1.75	Calibrated
Cost scale, λ	0.009	Calibrated
Cost curvature, ω	1.5	Calibrated

Table 9: Baseline parameter values

6.6 Model results

Baseline results

Figure 5 plots the main life-cycle profiles implied by the model: consumption and wealth, the portfolio share in risky assets, spending on financial knowledge, and the paths of actual and perceived financial knowledge.

The upper-left panel shows consumption and wealth over the life cycle. Consumption follows the standard hump-shaped pattern, rising during working life, flattening around retirement, and gradually declining at older ages. Wealth accumulates during the working years, peaks shortly after retirement, and then decumulates as households finance retirement consumption out of accumulated assets. These patterns are consistent with standard life-cycle models and with the empirical age profiles of income and wealth.

The upper-right panel reports the portfolio share in risky assets. After a brief ramp-up at entry, households hold a substantial risky share throughout the working life. The share

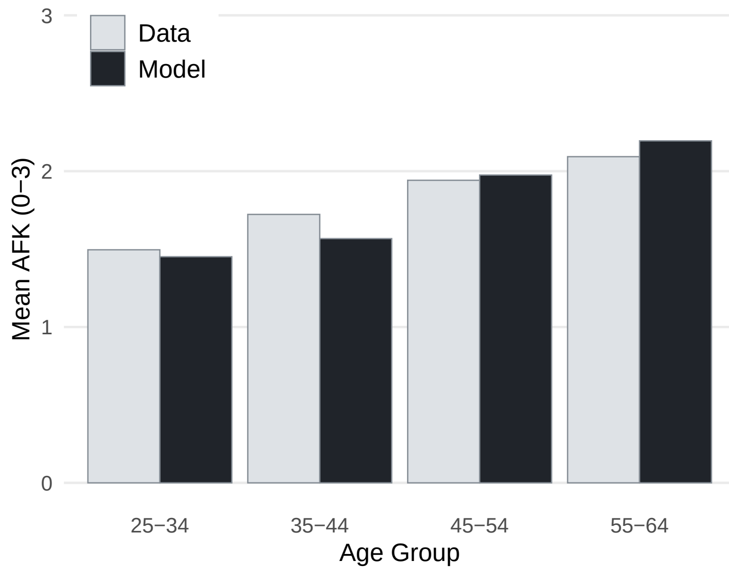

Figure 4: Model fit for actual financial knowledge over the life cycle. The figure compares NFCS age-specific averages to model-implied moments across the four working-age bins. The calibration targets these four AFK means.

declines only modestly through midlife and falls sharply after retirement as mortality risk rises and households shift toward safe wealth.

The lower-left panel shows investment in financial knowledge. Spending is concentrated in mid-career, when the remaining horizon over which higher expected returns can be enjoyed is still long; investment then declines as retirement approaches and falls to near zero by age 90.

The lower-right panel plots actual financial knowledge f alongside perceived financial knowledge f^P. At entry, perceived knowledge sits well above actual knowledge, reflecting the empirical degree of overconfidence in the NFCS at age 25. Bayesian learning gradually narrows the wedge over the life cycle, but does not eliminate it: the gap between perceived and actual knowledge persists into retirement, capturing the biased beliefs that survive even after decades of return signals.

Welfare cost of biased beliefs

The baseline life cycle shows the friction at work but says little about its consequences. To assess what biased beliefs cost households, I compare the baseline to a full-information benchmark in which $f_t^P = f_t$ at every age: households always observe their true knowledge and choose accordingly. Both economies are simulated under the same 10,000 income and return shock paths, so differences in outcomes come entirely from how households perceive

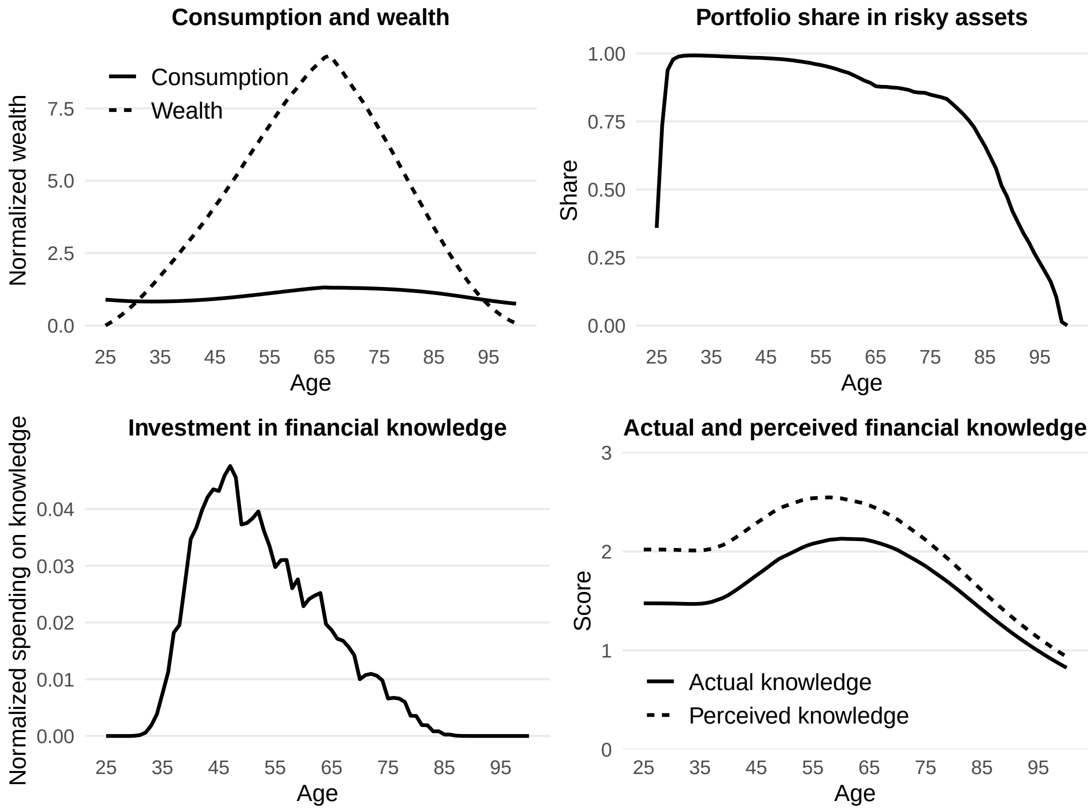

Figure 5: Baseline life-cycle profiles implied by the biased-belief model. The four panels plot simulated age profiles of average consumption and wealth (top left), portfolio share in risky assets (top right), investment in financial knowledge (bottom left), and actual versus perceived financial knowledge (bottom right).

their own knowledge.

The welfare cost is summarized by a consumption-equivalent variation (CEV). Let V_t^{FI} and V_t^{base} denote expected remaining lifetime utility at age t under the full-information and baseline economies. The lifetime CEV λ^L and retirement CEV λ^R solve

$$\mathbb{E}\sum_{s=t}^{T} \beta^{s-t}\,\pi_s\, u\big((1-\lambda)\,c_s^{\mathrm{FI}}\big) \;=\; \mathbb{E}\sum_{s=t}^{T} \beta^{s-t}\,\pi_s\, u\big(c_s^{\mathrm{base}}\big), \tag{17}$$

with $t = 25$ (lifetime) or $t = 66$ (retirement-only). A positive λ is the constant share of full-information consumption that, if surrendered, would leave the household indifferent between living under full information and living under the baseline biased beliefs. Biased beliefs cost households 1.72 percent of their retirement consumption relative to the full-information benchmark. Averaged over the entire life cycle, the loss appears negligible, only 0.08 percent of lifetime consumption, because wage income offsets biased portfolio and savings decisions during working life. Once that income stops, the cost of decades of biased choices is revealed.

That average hides wide dispersion in what households actually lose. Figure 6 plots the retirement consumption-equivalent variation for each of the 10,000 simulations. About three quarters of the simulated households reach retirement worse off under biased beliefs than under full information. Losses climb steeply through the upper tail. One household in ten loses more than 8.6 percent of its retirement consumption, and one in a hundred loses more than 23 percent.

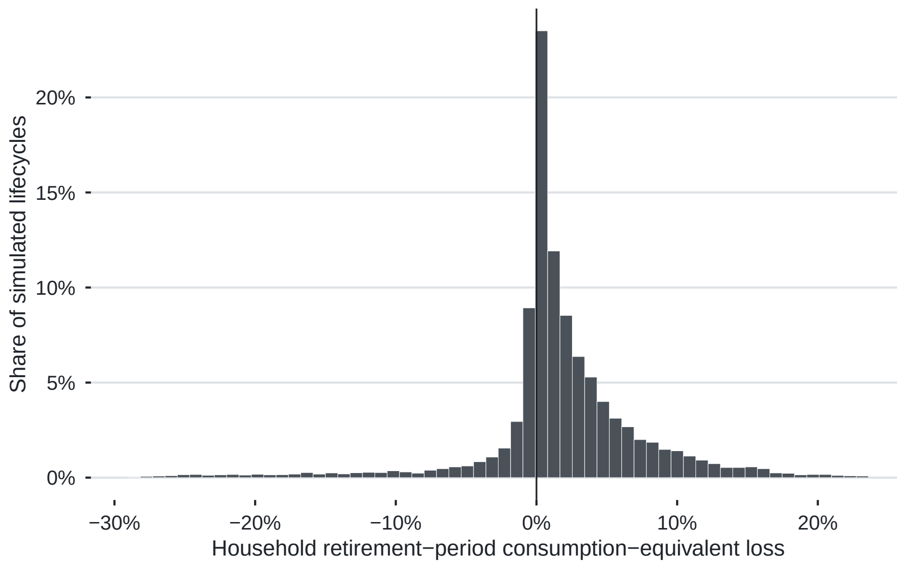

Figure 6: Distribution of the retirement welfare cost across households. Each observation is one simulated household's consumption-equivalent variation over the retirement period, measured against the full-information benchmark. Positive values are welfare losses; negative values are gains.

The spread reflects how biased beliefs expose households to risk. When a household believes it knows more than it does, it holds too much of the risky asset, and that leaves its retirement wealth to rise or fall with the returns it happens to draw. Biased beliefs therefore do more than lower welfare on average; they make the retirement outcome far more uncertain.

The risk grows with the entry belief gap, so a household that enters with accurate beliefs is barely exposed, while a sharply overconfident one carries a large position into a retirement that hinges on realized returns. The deepest losses require both a wide belief gap to enlarge the position and a poor run of returns to turn it against the household.

The cost does not come from knowing less. Actual knowledge accumulates almost identically under baseline and full information, and baseline households reach retirement with only about 1.5 percent less knowledge than the benchmark. What separates them is belief.

Baseline households enter retirement believing they know about 16 percent more than they actually do, and it is this belief gap that drives their portfolio and saving decisions.

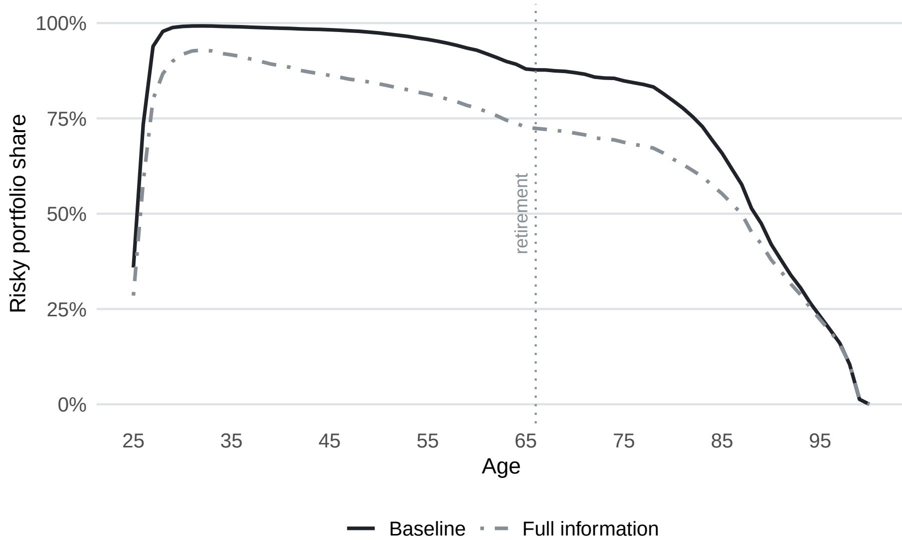

Figure 7: Risky portfolio share over the life cycle. Baseline households hold a higher risky share than full-information counterparts at every age. The vertical dotted line marks retirement entry at age 66.

Figure 7 shows the portfolio channel. Baseline households allocate close to their entire portfolio to the risky asset throughout the working life, averaging 95 percent and entering retirement at 88 percent risky. Full-information households are less aggressive at every age, averaging 83 percent and entering retirement at 73 percent. The gap between the two is persistent, about 12 percentage points across the working life.

As wealth accumulates, this portfolio-share gap translates into a larger absolute mismatch and a riskier retirement-wealth distribution. By retirement entry, the average biased-belief household holds 2.7 percent less wealth than its full-information counterpart, and exposes far more of that smaller stock to market risk.

Portfolio risk is the most visible distortion, but it is not the largest. Biased beliefs distort three margins of household behavior. They change how much the household invests in financial knowledge, how much it consumes and saves, and what share of its savings it places in the risky asset. A Shapley decomposition of the retirement welfare cost across these three margins attributes about 44 percent to distorted knowledge investment, 30 percent to distorted consumption and saving, and 26 percent to excess portfolio risk (Figure 8).

The knowledge channel dominates even though baseline and full-information households retire with almost the same knowledge stock. What is costly is not the terminal knowledge stock but the path of investment decisions taken under biased beliefs. No single margin

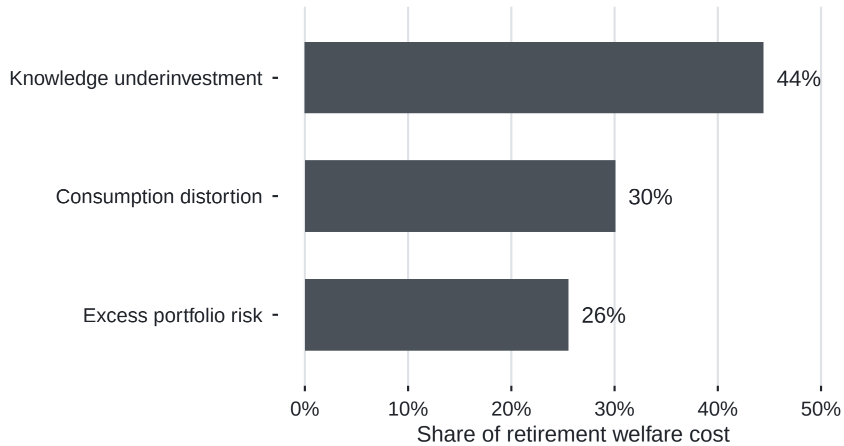

Figure 8: Shapley decomposition of the retirement welfare cost. Each bar is the share of total retirement consumption-equivalent variation attributable to one behavioral channel: investment in financial knowledge, consumption and saving, or the risky portfolio share.

carries the cost on its own. The welfare loss is the compound of all three.

The retirement cost traces almost entirely to what households believe at the start of the life cycle. A counterfactual that corrects only age-25 beliefs, and lets Bayesian updating proceed normally thereafter, recovers virtually all of the retirement welfare loss; the slow convergence of beliefs during adulthood adds almost nothing (see Appendix D). This maps directly onto the empirical identification in Section 4. Parental financial education shifts belief accuracy in childhood but does not directly affect later learning, so the instrument recovers the structural analog of correcting entry beliefs.

Figure 9 disaggregates the cost by the accuracy of entry beliefs. Households with accurate entry beliefs are barely affected, bearing a retirement loss of 0.19 percent. The cost climbs as beliefs grow less accurate in either direction. Overconfident households bear 2.34 percent and underconfident households 1.61 percent. Full information is the optimum, and a belief gap is costly whichever way it runs. Overconfidence is the prevalent case, and it is the one the empirical analysis addresses.

The empirical analysis and the model describe the same mechanism at two points in one causal chain. Section 4 identifies the downstream effect of overconfidence on financial outcomes such as retirement-account leakage and mortgage distress. The model supplies the upstream account. Biased beliefs raise risk-taking, hold down investment in financial knowledge, and distort the consumption path. These distortions compound into a riskier retirement-wealth distribution and lower welfare in old age. The reduced-form estimates establish that unjustified confidence is costly; the model traces how biased beliefs propagate over the life cycle and quantifies the welfare cost under the baseline calibration in Table 9.

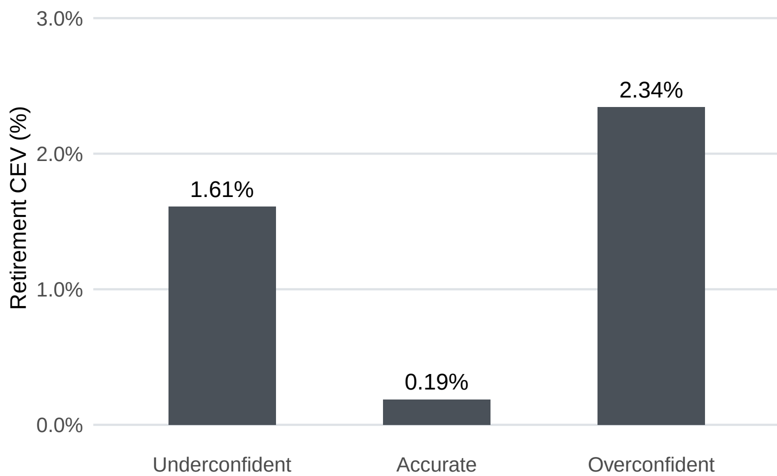

Figure 9: Welfare cost by the accuracy of entry beliefs. Households are grouped by the sign and magnitude of the entry wedge: overconfident if $f_{25}^P - f_{25} > 10$, accurate if $|f_{25}^P - f_{25}| \leq 10$, and underconfident if $f_{25}^P - f_{25} < -10$. Each bar is the population-weighted mean retirement CEV for households in that group.

7 Conclusion

Households often believe they know more about financial matters than they do. This paper asks what that gap costs them. Empirically, an IV strategy applied to the NFCS data shows that overconfidence in financial knowledge causally raises a broad set of adverse financial outcomes, from early retirement-account borrowing to mortgage and credit-card distress. To trace how these choices compound over a lifetime, I build a calibrated life-cycle portfolio-choice model in which households accumulate the wealth that funds retirement and form beliefs about their own financial knowledge from noisy returns. Biased beliefs distort that accumulation, and the resulting welfare loss concentrates in retirement.

I measure unjustified confidence as the part of perceived financial knowledge that test scores leave unexplained, and instrument it with an indicator for whether a respondent's parents taught them about money in childhood. The instrument's credibility relies on parental teaching shifting how confident adults feel without shifting what they actually know. A one-standard-deviation rise in unjustified confidence raises the probability of taking a loan from a retirement account by about 17 percentage points, with parallel effects on mortgage distress and credit-card overuse. The effect concentrates where households have the most room to act on their beliefs: those with low actual knowledge, men, and those who direct their own retirement-plan investments. Results are largely robust to alternative measures of overconfidence, and to controls and bounds that probe the exclusion restriction.

In the calibrated model, biased beliefs cost simulated households 1.72 percent of their retirement consumption. Wage income offsets the biased portfolio and saving decisions during working life. Once it stops, the cost of decades of biased choices surfaces. The loss is far from uniform: about three quarters of households reach retirement worse off, and one in ten loses more than 8.6 percent of retirement consumption. Biased beliefs leave households overexposed to market risk, so their retirement wealth hinges on the returns they draw. While portfolio risk is an important margin, biased beliefs also distort knowledge investment and the consumption path, and no single channel carries the cost alone.

The paper's two approaches measure the same object. In the model, correcting only the age-25 beliefs, with later learning left untouched, removes nearly all of the retirement loss, so the cost is carried by the belief gap households begin with. The instrument acts on exactly that gap: parental financial education shifts belief accuracy in childhood without altering later learning. The empirical effect and the structural welfare cost are therefore two windows on the same self-perception margin. The data catch the channel one decision at a time; the model follows it across a lifetime.

Plan-sponsor design and consumer-protection disclosure can target the self-perception margin where pure information cannot. The main policy implication is that financial education focused only on objective knowledge misses the same margin. While more knowledgeable households do judge themselves more accurately, programs should go beyond facts and build in feedback that shows households what they do not know. This matters most for low-knowledge households, whose overconfidence can overshadow the gains from knowledge alone. One caveat is that evidence on motivated beliefs shows that unwelcome signals are easily forgotten (Zimmermann, 2020), so such feedback must be designed carefully.

The welfare cost is, if anything, conservative. The model assumes Bayesian updating and omits default, borrowing, and leverage, important household-credit channels in which biased beliefs play a role. Adding those channels, or softening the Bayesian assumption, would raise the cost. One avenue for future research is to extend the model. Two others are to use panel data to reveal how overconfidence evolves with experience and shocks, and to draw on evidence from other periods and countries to show how widely the result holds.

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Appendix A Data

Summary statistics

Table A1: Sample summary statistics

Category	Mean (SD)	Share (%)
Age group (categorical)		
18-24		9.9
25-34		17.8
35-44		16.4
45-54		18.3
55-64		17.9
65+		19.8
Education level		
High school		48.0
No high school		1.5
University Degree		50.5
Employment status		
Full-time student		4.4
Homemaker		8.4
Permanently unable to work		3.8
Retired		21.3
Self-employed		7.3
Unemployed/Temporarily laid off		4.1
Work full-time		41.1
Work part-time		9.6
Ethnicity (categorical)		
Non-White		26.4
White		73.6
Gender (binary)		
Female		54.3
Male		45.7
Household income (categorical)		

Table A1: Sample summary statistics (continued)

Category	Mean (SD)	Share (%)
\$100,000 to \$149,999		13.4
\$15,000 to \$24,999		10.0
\$25,000 to \$34,999		10.4
\$35,000 to \$49,999		14.8
\$50,000 to \$74,999		21.4
\$75,000 to \$99,999		14.5
<\$15,000		8.9
>\$150,000		6.5
Marital status		
Married		56.9
Separated/Divorced/Widowed		16.1
Single		27.1
Has dependent children (binary)		36.9
Institutional financial education (binary)		23.1
Homeowner (binary)		66.1
Parental financial education (binary)		47.6
Debt burden (1–7, higher = more)	3.76 (2.26)	
Actual Financial Knowledge (0–3)	1.99 (1.00)	
Liquidity constraint (1–4, higher = worse)	2.00 (1.13)	
Perceived Financial Knowledge (1–7)	5.33 (1.15)	
Risk aversion (1–10, higher = more averse)	5.79 (2.63)	

Survey question wording

Actual financial knowledge (AFK)

AFK is based on three multiple-choice items in Section M of the NFCS:

1. **Interest compounding.** Respondents are asked to imagine having $100 in a savings account that earns 2% interest per year. If they leave the money there for five years and do not add any more, they must choose whether the balance will be more than $102, exactly $102, or less than $102.

2. **Inflation.** Respondents are asked to consider a savings account paying 1% interest per year when inflation is 2% per year. After one year, they must indicate whether the money in the account will buy more than today, the same as today, or less than today.

3. **Risk diversification.** Respondents are asked whether buying a single company's stock usually provides a safer return than a stock mutual fund, choosing between true and false.

Perceived financial knowledge (PFK)

PFK is based on the following self-assessment item:

> Using a scale from 1 to 7, where 1 means "very low" and 7 means "very high", respondents are asked how they would rate their overall financial knowledge.

I use the raw 1–7 response as the PFK measure, with higher values indicating greater perceived financial knowledge.

Parental financial education

Parental financial education is based on a single item in Section M of the NFCS, which asks whether the respondent's parents or guardians taught them how to manage their finances. The indicator equals one for respondents who answer yes.

Appendix B Heterogeneity and robustness

	AFK	PFK	UJC
Financial Edu (Parents)	-0.006 (0.012)	0.238*** (0.014)	0.240*** (0.014)
Financial Edu (Institution)	0.134*** (0.014)	0.296*** (0.015)	0.256*** (0.016)
Gender: Male	0.287*** (0.013)	0.056*** (0.014)	-0.025* (0.015)
Age: 25–34	0.077*** (0.027)	0.070** (0.031)	0.049 (0.032)
Age: 35–44	0.309*** (0.029)	0.079** (0.033)	-0.003 (0.034)
Age: 45–54	0.461*** (0.029)	0.075** (0.034)	-0.048 (0.034)
Age: 55–64	0.521*** (0.030)	0.223*** (0.035)	0.085** (0.036)
Age: 65+	0.583*** (0.033)	0.380*** (0.039)	0.221*** (0.040)
Ethnicity: White	0.168*** (0.016)	-0.064*** (0.017)	-0.109*** (0.018)
Education: University degree	0.615*** (0.049)	0.304*** (0.075)	0.140* (0.075)
Employment: Homemaker	-0.063 (0.039)	0.078 (0.048)	0.101** (0.048)
Employment: Unable to work	-0.114*** (0.044)	0.167*** (0.056)	0.207*** (0.056)
Employment: Retired	-0.070* (0.037)	0.223*** (0.046)	0.245*** (0.046)
Employment: Self-employed	0.010 (0.038)	0.221*** (0.047)	0.224*** (0.047)
Employment: Full-time	-0.044 (0.034)	0.113*** (0.042)	0.130*** (0.042)
Employment: Part-time	-0.096*** (0.037)	0.111** (0.046)	0.141*** (0.046)
Income: $15k–24k	0.053* (0.029)	0.073* (0.038)	0.062 (0.038)
Income: $25k–34k	0.032 (0.030)	0.129*** (0.038)	0.123*** (0.038)
Income: $35k–49k	0.164*** (0.029)	0.138*** (0.037)	0.100*** (0.037)
Income: $50k–74k	0.206*** (0.029)	0.108*** (0.037)	0.055 (0.037)
Income: $75k–99k	0.263*** (0.032)	0.124*** (0.039)	0.054 (0.039)
Income: $100k–149k	0.380*** (0.033)	0.107*** (0.040)	0.000 (0.040)
Income: >$150k	0.437*** (0.037)	0.178*** (0.043)	0.052 (0.044)
Risk Aversion	0.000 (0.003)	-0.112*** (0.003)	-0.110*** (0.003)
Debt Level	-0.011*** (0.003)	-0.027*** (0.004)	-0.024*** (0.004)
Liquidity Constraint	-0.096*** (0.007)	-0.131*** (0.008)	-0.105*** (0.008)
Marital: Sep./Div./Widowed	0.029 (0.022)	0.109*** (0.026)	0.103*** (0.027)
Own home	-0.040*** (0.015)	0.146*** (0.018)	0.156*** (0.018)
Dependent children	-0.128*** (0.015)	0.086*** (0.017)	0.120*** (0.017)
Num.Obs.	23343	23343	23343
R2	0.223	0.221	0.170
State fixed effects	Yes	Yes	Yes

Table B1: Full regression of AFK, PFK, and UJC on parental financial education and all controls. Heteroskedasticity-robust standard errors in parentheses.

	Retirement loan		Retirement withdrawal	
	(1)	(2)	(3)	(4)
Panel A: Investment discretion				
	Self-directs	Manager-directed	Self-directs	Manager-directed
UJC	0.217***	0.048	0.217***	-0.006
	(0.042)	(0.069)	(0.037)	(0.066)
Controls	Yes	Yes	Yes	Yes
Observations	9,412	1,463	9,412	1,463
First-stage F	93.0	13.3	93.0	13.3
Panel B: Independent retirement-account ownership				
	Has IRA	No IRA	Has IRA	No IRA
UJC	0.231***	0.017	0.220***	0.020
	(0.053)	(0.048)	(0.049)	(0.036)
Controls	Yes	Yes	Yes	Yes
Observations	8,906	3,982	8,906	3,982
First-stage F	53.4	51.0	53.4	51.0
Panel C: Gender				
	Men	Women	Men	Women
UJC	0.278***	0.100***	0.279***	0.098***
	(0.087)	(0.033)	(0.078)	(0.028)
Controls	Yes	Yes	Yes	Yes
Observations	6,576	6,426	6,576	6,426
First-stage F	26.0	100.8	26.0	100.8

Table B2: IV estimates of the effect of UJC on retirement-account leakage, by investment discretion (Panel A), independent retirement-account ownership (Panel B), and gender (Panel C). Heteroskedasticity-robust standard errors in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls and state fixed effects as in Equation 2. Subsample sizes in Panels A and B do not sum to the full retirement subsample (13,002) because of item nonresponse on the splitter.

	Retirement loan		Retirement withdrawal	
	AFK ≤ 1	AFK ≥ 2	AFK ≤ 1	AFK ≥ 2
	(1)	(2)	(3)	(4)
Reduced form: Parental.FinEdu $\rightarrow$ Y	0.091***	-0.001	0.077***	-0.001
	(0.014)	(0.005)	(0.013)	(0.004)
First stage: Parental.FinEdu $\rightarrow$ UJC	0.220***	0.122***	0.220***	0.122***
	(0.036)	(0.015)	(0.036)	(0.015)
Implied $\widehat{\beta}_1$ (RF / FS)	0.414	-0.008	0.351	-0.007
Observations	2,804	10,198	2,804	10,198

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Heteroskedasticity-robust standard errors in parentheses.

Table B3: Reduced-form and first-stage regressions on retirement-account leakage outcomes, split by AFK subsample. The implied 2SLS coefficient (reduced form divided by first stage) reproduces the IV magnitudes in Table 4.

	Retirement		Mortgage		Credit card	
	Loan	Withdrawal	Underwater	Late	Cash advance	Over-limit
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS						
UJC	0.024***	0.027***	0.014***	0.011	0.018***	0.014***
	(0.003)	(0.003)	(0.005)	(0.008)	(0.003)	(0.002)
Panel B: Reduced form						
Parental financial education	0.026***	0.026***	0.021***	0.027**	0.009**	0.014***
	(0.005)	(0.004)	(0.007)	(0.011)	(0.004)	(0.003)
Panel C: 2SLS						
UJC	0.167***	0.166***	0.109***	0.145**	0.050**	0.073***
	(0.034)	(0.030)	(0.040)	(0.061)	(0.023)	(0.019)
First-stage F	118.3	118.3	102.4	102.4	214.5	214.5
AFK	Yes	Yes	Yes	Yes	Yes	Yes
Controls + state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,002	13,002	8,458	8,458	19,287	19,287

Table B4: OLS, reduced-form, and 2SLS estimates of the effect of unjustified confidence on the six headline outcomes. Columns are separate subsamples (retirement-account, mortgage, and credit-card holders) estimated with the main-text controls and state fixed effects. Panels A and C report the coefficient on UJC per standard deviation; Panel B reports the coefficient on the binary parental-financial-education instrument, so its magnitude is not directly comparable. Heteroskedasticity-robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Underwater mortgage (1)	Late mortgage (2)	CC cash advance (3)	CC over-limit (4)
Panel A: Low AFK (≤ 1)				
UJC	0.313***	0.307***	0.150***	0.152***
	(0.075)	(0.105)	(0.044)	(0.040)
Controls	Yes	Yes	Yes	Yes
Observations	2,143	2,143	5,247	5,247
First-stage F	51.4	51.4	80.7	80.7
Panel B: High AFK (≥ 2)				
UJC	-0.143**	-0.140	-0.042	-0.011
	(0.061)	(0.089)	(0.028)	(0.021)
Controls	Yes	Yes	Yes	Yes
Observations	6,315	6,315	14,040	14,040
First-stage F	40.1	40.1	117.5	117.5

Table B5: IV estimates of the effect of UJC on the non-retirement outcomes, by AFK subsample (AFK ≤ 1 vs AFK ≥ 2).

	Retirement loan (1)	Retirement withdrawal (2)	Underwater mortgage (3)	Late mortgage (4)	CC cash advance (5)	CC over-limit (6)
Panel A: Has formal financial education						
UJC	0.264***	0.220***	0.058	0.265*	0.161**	0.133**
	(0.088)	(0.077)	(0.090)	(0.151)	(0.069)	(0.058)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,425	3,425	2,087	2,087	4,568	4,568
First-stage F	25.2	25.2	21.7	21.7	34.4	34.4
Panel B: No formal financial education						
UJC	0.129***	0.146***	0.111**	0.092	0.022	0.058***
	(0.035)	(0.031)	(0.044)	(0.067)	(0.023)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,577	9,577	6,371	6,371	14,719	14,719
First-stage F	95.6	95.6	79.8	79.8	181.2	181.2

Table B6: IV estimates of the effect of UJC on retirement-account leakage and the non-retirement outcomes, by formal financial-education exposure.

	(1) Baseline	(2) Big Six AFK	(3) DK-adjusted	(4) Relatives controls
Underwater mortgage	0.109***	0.105***	0.122***	0.080**
	(0.040)	(0.036)	(0.046)	(0.040)
N	8,458	8,458	8,458	8,458
Wald (1st stage), UJC	102.4	104.6	65.2	97.1
Late mortgage	0.145**	0.139**	0.162**	0.079
	(0.061)	(0.056)	(0.070)	(0.061)
N	8,458	8,458	8,458	8,458
Wald (1st stage), UJC	102.4	104.6	65.2	97.1
CC cash advance	0.050**	0.049**	0.054**	0.029
	(0.023)	(0.021)	(0.024)	(0.022)
N	19,287	19,287	19,287	19,287
Wald (1st stage), UJC	214.5	214.1	162.2	213.9
CC over-limit fee	0.073***	0.071***	0.078***	0.051***
	(0.019)	(0.018)	(0.020)	(0.018)
N	19,287	19,287	19,287	19,287
Wald (1st stage), UJC	214.5	214.1	162.2	213.9

Table B7: Alternative specifications: non-retirement outcomes. Each panel reports the 2SLS coefficient on UJC (heteroskedasticity-robust standard error in parentheses) for one outcome under four UJC constructions: (1) baseline UJC, (2) UJC built on the Big Six AFK, (3) UJC adjusted for don't-know count, and (4) baseline UJC with additional controls for transfers from relatives and co-residence with parents. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls and state fixed effects as in Equation 2.

	2SLS estimate	Eff. F	AR 95% set	Bonferroni	Romano-Wolf
Retirement loan	0.167*** (0.037)	102	[0.096, 0.244]	<0.001	<0.001
Retirement withdrawal	0.166*** (0.038)	102	[0.096, 0.246]	<0.001	<0.001
Underwater mortgage	0.109** (0.041)	122	[0.030, 0.192]	0.036	0.015
Late mortgage	0.145** (0.068)	122	[0.011, 0.281]	0.110	0.034
CC cash advance	0.050** (0.025)	227	[0.002, 0.100]	0.154	0.034
CC over-limit fee	0.073*** (0.024)	227	[0.027, 0.123]	<0.001	0.001

Table B8: Inference robustness for the six headline IV estimates. Columns report the 2SLS coefficient on UJC (per standard deviation, state-clustered standard error in parentheses), the Olea-Pflueger effective first-stage F, the Anderson-Rubin weak-instrument-robust 95 percent confidence set, and Bonferroni and Romano-Wolf p-values over the six-outcome family (1,000-rep nonparametric household-level bootstrap; (Romano and Wolf, 2005)). Subsample sizes vary by outcome.

Appendix C Conley bounds

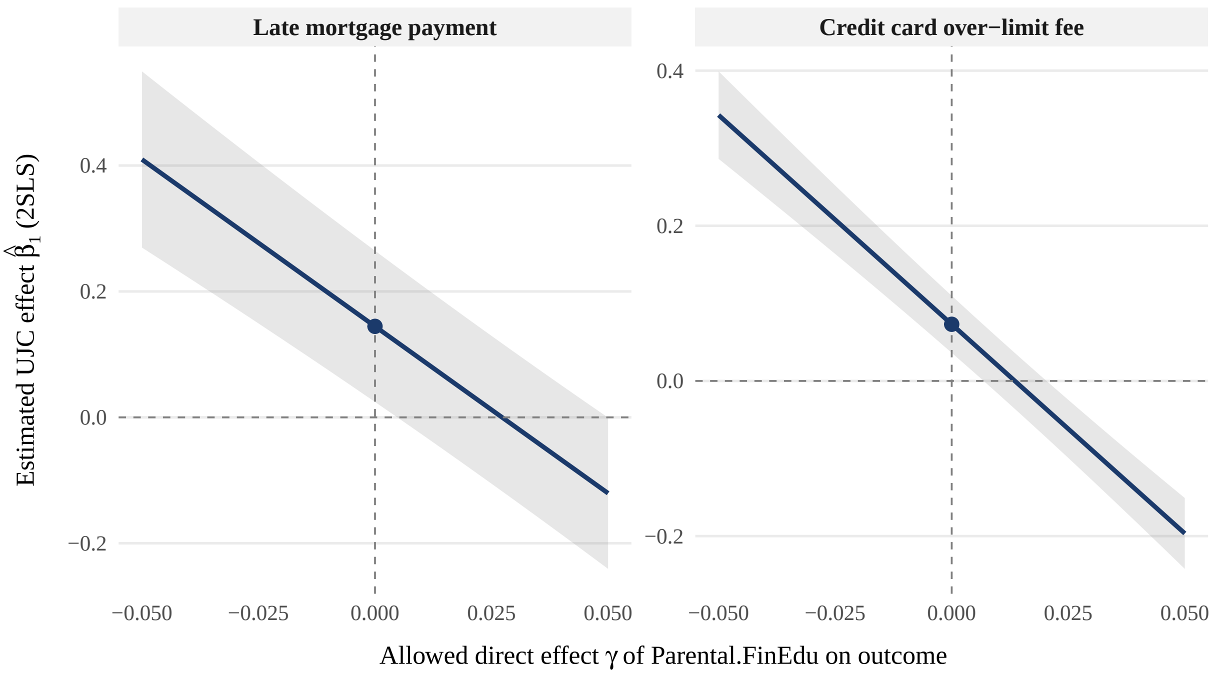

Figure C1: Conley plausibly exogenous bounds for $\widehat{\beta}_1$, as in Figure 3, for two further outcomes: late mortgage payment and credit-card over-limit fee.

Appendix D Welfare decomposition: entry beliefs vs Bayesian learning

To isolate how much of the welfare cost of biased beliefs arises from entry-period misperception, I run a third counterfactual alongside the baseline and the full-information benchmark described in Section 6.6. This policy counterfactual sets $f^P_{25} = f_{25}$ at entry and lets Bayesian updating proceed normally thereafter, so it corrects the initial belief but leaves later belief formation unchanged. It is the structural analog of a childhood intervention that aligns perceived and actual knowledge at age 25 without altering subsequent learning.

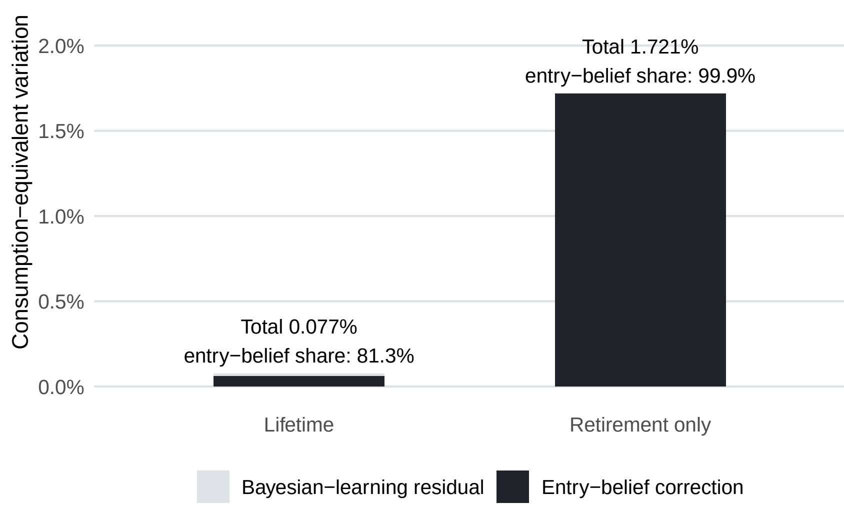

Figure D1: Decomposition of the welfare cost. Entry-belief correction (dark) is the share of the welfare loss reported above each bar; the remainder (light grey) is what Bayesian learning during the working life recovers.

Correcting entry beliefs alone captures 81.3 percent of the lifetime welfare loss and 99.9 percent of the retirement-period loss. Bayesian learning from observed returns over the working life contributes almost nothing on top. The result implies that essentially all of the welfare cost identified in Section 6.6 can be traced to what households believe at age 25.