From Learning to Earning:
Financial Literacy and Wealth Accumulation in the UK

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Abstract

Only 22% of UK households hold stocks. Even among those with substantial savings, many keep the majority of their wealth in low-yield cash accounts. This paper argues that financial-literacy frictions, rather than monetary participation costs, are central to understanding who participates in equity markets and how they allocate wealth. Using the FCA Financial Lives Survey, we show that, conditional on wealth, stock-market participation is strongly increasing in financial literacy, while the share of the portfolio held in cash falls with literacy. We also document that large, early-life literacy gaps by gender and education narrow with the amount invested in non-cash assets, consistent with learning-by-doing. We develop a calibrated life-cycle model in which literacy is a non-monetary participation friction that accumulates endogenously through stock-market experience. The model reproduces the imperfect wealth–participation correlation observed in the data, with some high-literacy, low-wealth households entering and some high-wealth, low-literacy households remaining out. Policy experiments show that early-life literacy interventions and stock (rather than cash) transfers can raise long-term participation, literacy, and retirement consumption, enhancing resilience to income shocks while increasing exposure to financial shocks.

Keywords: Learning-by-doing, Financial Literacy, Stock Participation, Household Finance.

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1 Introduction

Over the past decade, global equities have delivered average annual returns of around 9%, compared with roughly 0.9% on UK cash deposit accounts. Yet only around one-in-five UK households hold stocks as part of their savings and investment portfolio. One might suspect that most households simply lack the balances required to invest in risky assets. However, among the roughly 40% of households with more than £10,000 in savings and investments, 38% keep the entirety of these assets in cash. These patterns suggest that many households, including relatively wealthy ones, systematically forgo the higher expected returns available on equity investments in favor of low-yield cash accounts.

A standard explanation for limited stock-market participation is the presence of fixed or per-trade entry costs, which can make stock-holding unattractive for households with modest wealth. In the current UK environment, however, this explanation is less compelling. Over the past decade, the expansion of commission-free trading platforms has sharply reduced direct participation costs. Trading 212 and Freetrade, for example, have offered commission-free trading accounts in the UK since 2018 and allow households to open an account with as little as £1. These developments suggest that non-price frictions, rather than explicit trading costs, may play a more central role in keeping a large share of assets in cash rather than in higher-return equity assets.

In this paper, we will study the role of financial literacy frictions in shaping both the extensive and intensive margins of stock-market participation, and we analyze how learning-by-doing through stock-holding can narrow literacy gaps over the life cycle, improving household outcomes. Using new evidence from the FCA Financial Lives Survey, we document how financial literacy varies across households and how it interacts with participation, portfolio composition, and wealth. We then embed these empirical patterns in a life-cycle model with endogenous financial literacy, where literacy operates as a non-monetary participation friction and accumulates through experience in equity markets.

Financial literacy is highly heterogeneous across households and strongly related to investment behavior (see, e.g., van Rooij et al., 2011). We find large gaps by gender and education, in line with Cota et al. (2025), and these gaps are tightly linked to both stock-market participation and portfolio composition. Conditional on wealth, participation is monotonically increasing in the number of correct answers to the standard literacy questions, while the share of the portfolio held in cash declines sharply with literacy. Among households with more than £50,000 in investable assets, participation rises from roughly one-fifth when no literacy questions are answered correctly to more than one-half when all four are correct. On the intensive margin, even those with more than £250,000 in assets hold about 70% of their portfolio in cash when they score 0–1 out of four, compared with roughly 45% when they score four out of four.

We also show that, conditional on investing in non-cash assets, financial literacy gaps *narrow* with the amount invested. For households with more than £10,000 in investable assets, but held entirely in cash, the predicted literacy gap between men and women is around 0.3 correct responses. This gap shrinks as non-cash holdings rise, falling to around 0.18 at £100,000 of non-cash investments and nearly disappearing by £250,000. Similar patterns hold across education groups. These facts are consistent with a learning-by-doing mechanism, in which stock-market experience builds financial literacy over time and gradually reduces the informational disadvantages of initially less literate groups.

The notion of limited participation goes back to Mankiw and Zeldes (1991) and Haliassos and Bertaut (1995), with the latter hypothesizing the role of informational frictions. Much of the subsequent quantitative literature has represented these frictions as monetary participation costs, either fixed entry fees or per-period holding costs (see, e.g., Alan, 2006; Vissing-Jorgensen, 2002). While such costs can rationalize low participation among low-wealth households, they struggle to explain why many high-wealth households still avoid equities or hold only small positions, especially now that explicit trading fees have largely disappeared. They also imply a tight wealth–participation link that is at odds with the empirical coexistence of low-wealth but high-literacy stockholders and high-wealth but low-literacy non-participants.

A related strand of work endogenizes financial knowledge. Lusardi et al. (2017) develop an influential life-cycle model in which households spend monetary resources on financial knowledge that raises the return on sophisticated assets, amplifying wealth inequality; Cota et al. (2025) apply a similar framework to study gender gaps. In these settings, acquiring literacy is primarily a budgetary choice tightly linked to income and wealth, and learning-by-doing is captured in reduced form, for example, through an indicator for holding any risky asset. By contrast, empirical work such as Frijns et al. (2014) and Mandell (2008) show that hands-on experience with financial products and stock-market games can be especially effective in raising literacy, over and above classroom-style training, and Cota et al. (2025) find that life-cycle events (such as divorce, spousal illness, or widowhood) raise women's literacy in a way consistent with learning-by-doing.

Our empirical evidence and modeling approach build on and extend these insights in three ways. First, on the data side, we document that, even after controlling for wealth and other observables, financial literacy is monotonically related to both stock-market participation and the share of wealth held in non-cash assets, and that literacy gaps by gender and education narrow with the amount invested in risky assets. Using inheritances as an instrument for stock-holding in an endogenous ordered-probit model, we show that stock-market participation has a sizable positive effect on financial literacy, with particularly strong effects for women and for households without a university degree, providing direct evidence of learning-by-doing in household financial decision-making.

Second, we develop a partial-equilibrium life-cycle model in which households choose consumption, cash, and equity holdings, and financial literacy evolves endogenously through a learning-by-doing mechanism. Literacy acts as a non-monetary participation friction, entering the decision problem through the perceived costs and complexity of stock-market participation rather than through the budget constraint. Low-literacy households face high costs of entering or expanding stock positions, whereas high-literacy households find it easy to participate even when wealth is modest. Learning-by-doing raises literacy both from holding stocks and from increasing stock positions, making additional investment easier. Calibrated to the Financial Lives Survey and the Wealth and Assets Survey, the model reproduces this imperfect correlation between wealth and participation.

Third, we use the model to study policy and aggregate implications of endogenous financial literacy, focusing on age-targeted literacy interventions, equal-sized cash versus stock transfers, and aggregate income and return shocks. Literacy programs that raise latent literacy by 25% have modest but systematically larger effects when delivered earlier in life, because they generate more years of participation and learning-by-doing. Cash transfers of realistic size have negligible long-run effects on participation and literacy, whereas stock transfers have powerful and persistent effects: they mechanically induce entry, push households along the learning-by-doing curve, and raise participation, literacy, and consumption at retirement. Higher literacy and participation also improve resilience to income shocks, as households enter downturns with higher wealth and smoother consumption, but at the cost of greater exposure to rare asset-price crashes and larger short-run consumption drops after adverse return shocks.

This paper highlights the importance of non-monetary financial literacy frictions and learning-by-doing for understanding who participates in equity markets, how much risk they take, and how policy interventions translate into participation and wealth. By jointly matching the extensive and intensive margins of stock-holding and the evolution of literacy gaps over the life cycle, the paper complements the literature on limited participation and monetary participation costs, and contributes to a growing body of work that places financial knowledge and experience at the center of household portfolio behavior.

2 Data

Both the empirical analysis and model calibration draw on two UK household datasets. Our primary source is the FCA Financial Lives Survey 2022 (FLS; FCA, 2022), which we use to study the joint distribution of financial literacy, wealth, and stock-holding. In addition, we use the UK Wealth and Assets Survey (WAS; Office for National Statistics, 2023), a longitudinal survey with information on the monetary amounts of assets, debts, and incomes. Although the WAS does not contain literacy measures, it is well suited for documenting portfolio composition and calibrating income and wealth dynamics.

2.1 Financial Lives Survey

The Financial Lives Survey (FLS) is a repeated cross-section that collects information on UK adults' financial products, behaviors, and attitudes. A key feature for our purposes is the inclusion of four standard financial literacy questions based on Lusardi and Mitchell (2008). The questions cover simple and compound interest, inflation, and risk diversification; correct responses indicate understanding of these topics. The exact wording and response options are reported in Appendix A.1. Beyond literacy, the FLS records ownership of a wide range of financial products (e.g., savings accounts, bonds, cryptocurrencies, and investment property). It also contains categorical measures of "investable assets", the share of these assets held in cash, and standard demographic and behavioral characteristics.

The FLS asks respondents about their level of investable assets, defined as the sum of liquid savings held in current accounts and cash savings products (such as savings accounts and cash ISAs), plus the current market value of any investment products held. This measure excludes primary residences and defined contribution pension assets, but includes investment properties. Individuals with joint savings or investments are instructed to report only the share they consider to be personally theirs (FCA, 2023). The distribution can be seen in Figure A1. Around 38% of households report at least £10,000 in investable assets, while roughly 35% hold less than £1,000. As investable assets exclude cash for spending needs, low balances do not mechanically imply binding liquidity constraints, although they suggest limited financial resilience and exposure to income or expenditure shocks, given the absence of a substantial precautionary buffer.

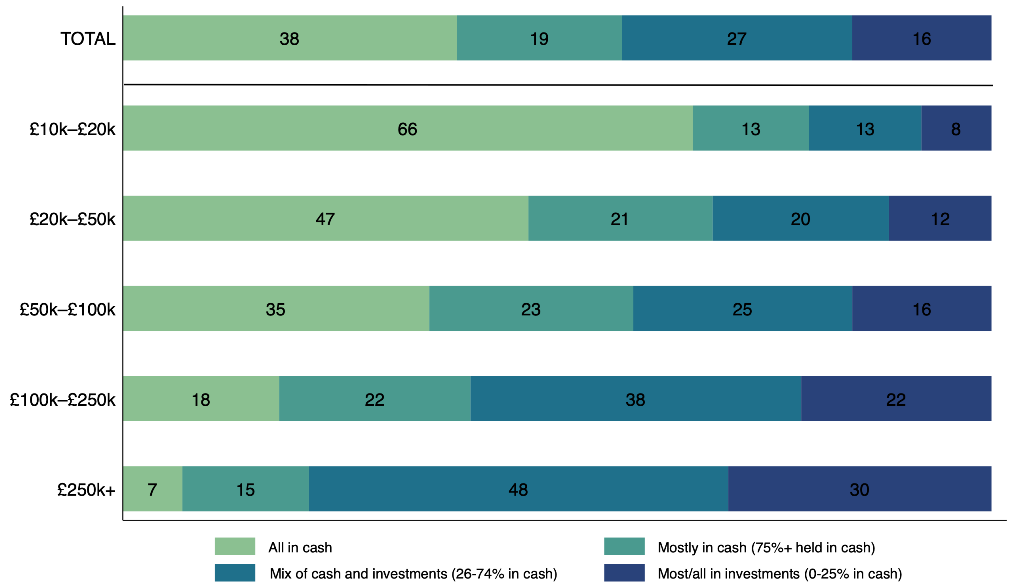
For households with investable assets above £10,000, the FLS asks about the "propensity to invest" in non-cash assets, that is, a response to a categorical question on percentage of portfolio held in cash.[1] Figure 1 shows the distribution of these responses by asset group. Even in this higher-wealth subsample, around 38% hold all of their investable assets in cash, and a further 19% hold at least three-quarters in cash. This pattern points to a strong preference for cash assets, even among households with non-trivial wealth.

2.2 Wealth and Assets Survey

The Wealth and Assets Survey (WAS) is a longitudinal survey that tracks UK households' assets, debts, and incomes over time. As households can be followed across waves, the WAS is particularly useful for characterizing income dynamics and the evolution of portfolio composition. We use these moments to calibrate the income process and the allocation between cash and risky assets in our model (Section 4.3).

[1] The "propensity to invest" question is asked only of respondents with more than £10,000 in investable assets; comparable information is therefore unavailable for households with smaller balances.

Figure 1: Propensity to Invest by Investable Assets Category



Notes: The figure reports, for each category of investable assets above £10,000, the fraction of households responding to each category of "propensity to invest": (1) All in cash, (2) Mostly in cash (75%+ in cash), (3) Mix of cash and investments (26–74% in cash), (4) Mostly in investments (0–25% in cash).

Table 1 reports summary statistics for key income and wealth variables in Wave 7 (2020). Average gross household income is around £44.1k, with substantial dispersion (standard deviation £41.3k). Net property wealth is the largest component of net wealth, with a mean of £264.2k and a median of £190k, while net financial wealth averages £100.5k but has a median of only £25.6k. Within financial wealth, cash and deposits are the dominant and most widely held asset, with a median of about £14k, whereas direct holdings of stocks and bonds are concentrated among a minority of households, consistent with limited direct market participation. Conditional on holding financial assets, the typical household holds roughly £10 in cash for every £1 in equities.

Table 1: Descriptive Statistics of Household Income and Wealth in 2020 (in £000s)

	Mean	**Std. Dev.**	**P10**	**P50**	**P90**	**N**
Income						
Gross income	44.1	41.3	13.0	33.7	85.3	11,341
Net Wealth						
Property wealth	264.2	327.4	0.0	190.0	600.0	11,341
Financial wealth	100.5	244.9	-2.0	25.6	284.0	11,340
Financial Assets						
Stocks	4.5	20.5	0.0	0.0	5.0	11,341
Bonds	8.5	53.9	0.0	0.0	10.5	11,341
Cash and deposits	44.5	86.4	0.3	14.0	118.8	11,341

Notes: Table reports descriptive statistics for household income and wealth variables for the Wealth and Assets Survey Wave 7. All amounts are expressed in £ thousands. Property and financial wealth are measured net of associated liabilities (e.g., mortgages on property).

3 Financial Literacy and Learning-by-Doing

In this section, we document how financial literacy varies across population subgroups and how it relates to stock-market participation and portfolio composition. We first describe cross-sectional patterns in literacy by gender, education, and stock-holding status, and we show that financial literacy is strongly associated with both the extensive margin of stock-market participation and the intensive margin of non-cash investment. We then examine how literacy gaps by gender and education evolve with investment intensity, and finally we use an instrumental-variable strategy based on recent inheritances to estimate the effect of stock-market participation on financial literacy.

As has been widely documented in the literature, there is substantial heterogeneity in financial literacy across subgroups. This pattern is evident in Table 2, which reports mean financial literacy scores by gender, education, stock ownership, and recent inheritance status (the latter will be revisited in Section 3.3). Consistent with Cota et al. (2025), women display systematically lower financial literacy than men: on average, men answer 3.29 out of four questions correctly, compared with 2.80 for women. Panel B further shows that individuals with higher education have higher literacy, in line with van Rooij et al. (2011), and that the gender gap persists within each educational category.

Although this paper focuses on stock-market participation, we see that stock-holding is correlated with holdings of other asset classes. Appendix A.4 shows that households with stocks are much more likely to hold other risky assets such as stocks and shares ISAs, corporate or government bonds, buy-to-let property, and other real assets. For example, 16.7% of stockholders hold investment property compared with 5.0% of non-stockholders, 6.9% hold cryptocurrency compared with 2.0%, and 10.6% hold other real assets compared with 3.5%. Additionally, we find similar participation patterns across wealth and literacy as those observed with stocks (see Figure A2). These differences suggest that stock-holding is a useful summary indicator of broader engagement with risky assets.

Table 2: Mean Financial Literacy Scores by Demographic Group and Interactions

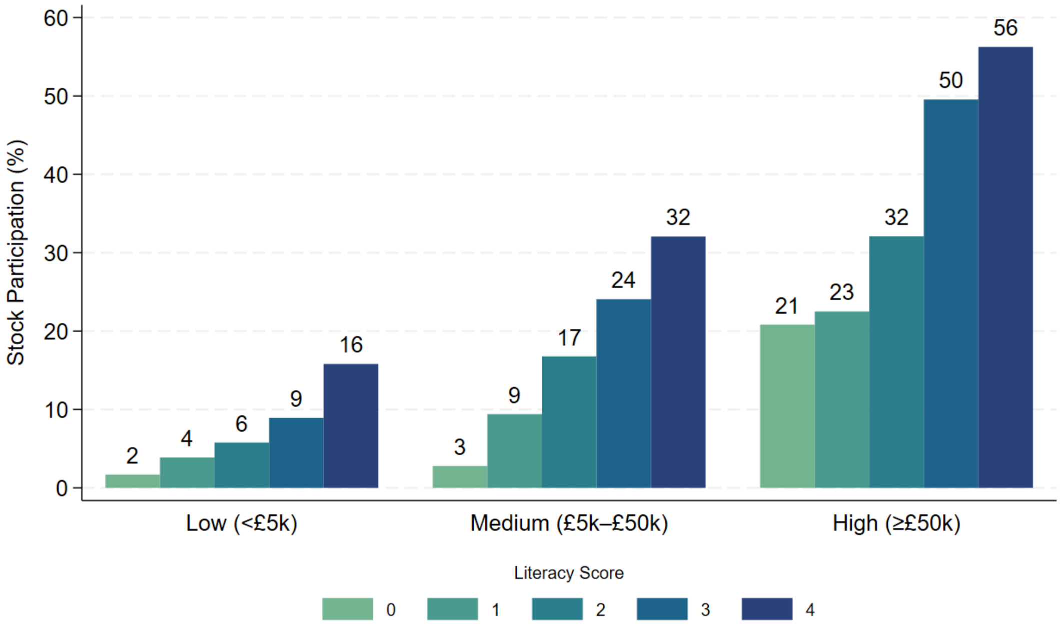
	Mean	**Std. Dev.**	**N**
A. Gender			
Male	3.29	0.95	14,717
Female	2.80	1.09	13,340
B. Gender × Education Level			
Lower Secondary			
Male	2.93	1.07	2,016
Female	2.54	1.11	2,290
Overall	2.72	1.11	4,337
Upper Secondary			
Male	3.22	0.95	4,280
Female	2.71	1.09	3,427
Overall	2.99	1.05	7,763
Tertiary			
Male	3.58	0.75	7,667
Female	3.07	1.01	6,949
Overall	3.34	0.91	14,759
C. Stock Ownership			
No Stocks	2.91	1.08	20,467
Has Stocks	3.52	0.76	7,824
D. Inheritance Status			
Received Inheritance	3.38	0.90	949
No Inheritance	3.04	1.05	27,369

Notes: Table reports mean financial literacy scores and distributional statistics (standard deviation and 25th, 50th, and 75th percentiles) by demographic characteristics, education level, inheritance, and stock ownership. Gender–education interaction values are computed from group-level data.

3.1 Extensive-Margin Patterns

Financial literacy plays an important role in stock-market participation, and the evidence points to effects on both the extensive and intensive margins of stock-holdings. We begin with the extensive margin. Figure 2 shows stock-market participation rates by aggregated investable-asset group and by financial literacy score. As expected, participation increases monotonically across wealth groups: the average participation rates in the low-, medium-, and high-asset groups are 6.2%, 26.2%, and 53.1%, respectively. More striking, however, is the heterogeneity *within* asset groups. Among respondents with more than £50,000 in investable assets, only 21% of those who answer none of the four financial literacy questions correctly hold stocks, compared with 56% among those who answer all four correctly. Similar patterns hold across the other wealth groups: participation rises from 2% to 16% in the low-asset group and from 3% to 32% in the medium-asset group as financial literacy increases from zero to four correct answers. Furthermore, even among households with less than £1,000 in assets, 5% of those with the highest literacy scores hold stocks.

Figure 2: Stock Participation by Investable Assets and Financial Literacy Score



Notes: Figure plots the stock-market participation rate in subgroups of investable assets by financial literacy score. Investable-asset groups are defined as: low, under £5,000; medium, £5,000 to £49,999; high, above £50,000. The average participation rates across groups are 6.2%, 26.2%, and 53.1%, respectively. The average financial literacy scores across groups are 2.7, 3.2, and 3.6, respectively.

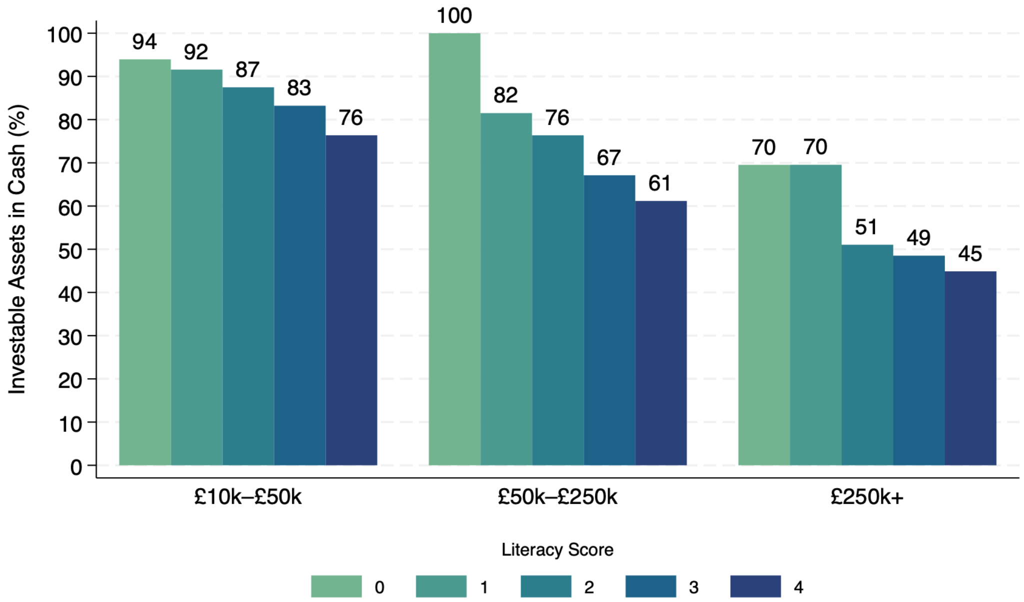
The contrast within the high-asset group is particularly informative for understanding extensive-margin barriers to participation. Financial costs may plausibly deter stock-market entry among low-wealth households; however, they cannot account for the persistently low participation among wealthy individuals with very low literacy. Instead, these patterns point to non-monetary frictions, most notably limited financial literacy, as a key barrier to stock-market participation.

3.2 Intensive-Margin Patterns

We now turn to the intensive margin. As the FLS does not directly record the monetary value of households' non-cash investments, we construct an *approximation* using the available categorical information. For respondents with investable assets above £10,000, we interact the midpoints of the investable-asset categories with the midpoints of the reported "propensity to invest" categories, truncating investable assets at £250,000 for the highest bracket. A more detailed description of the underlying bins and their interaction is provided in Appendix A.3. For example, a respondent reporting investable assets between

£10,000 and £20,000 and indicating that their savings are held "mostly in cash" (that is, at least 75% in cash) is assigned an asset midpoint of £15,000 and a non-cash investment share of 12.5%, implying an estimated non-cash investment value of £1,875. This procedure yields an internally consistent proxy for non-cash investment holdings that preserves the ordinal variation implied by the categorical responses, and one can interpret this as a proxy for stock-holding intensity.

Figure 3: Cash Asset Percentage by Investable Assets and Financial Literacy Score



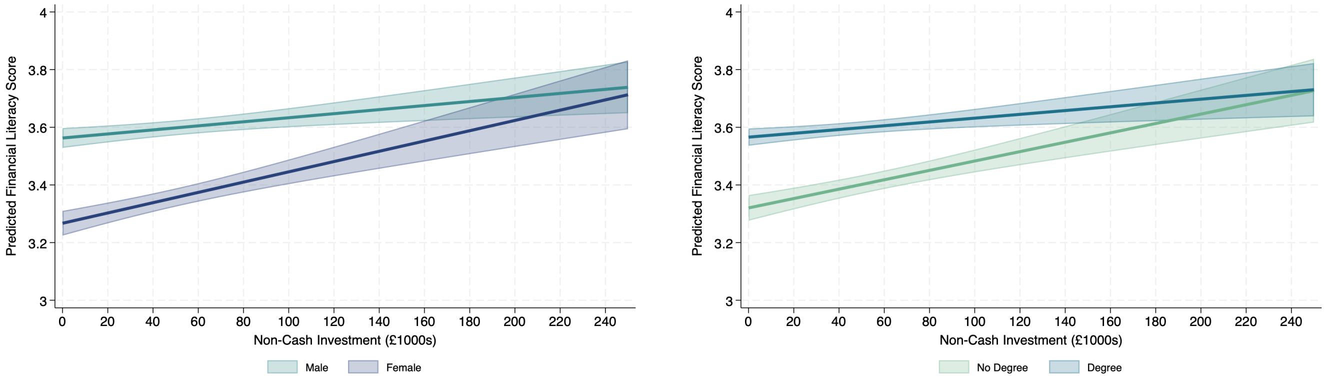
Notes: Figure plots the average percentage of investable assets held in cash by investable-asset group and financial literacy score. Investable-asset groups are defined as in Appendix A.3, and financial literacy scores range from 0 to 4.

Figure 3 tells a similar story to that of Figure 2: average cash shares decline with the level of investable assets, but there is substantial within-group variation in cash holdings by financial literacy. Households with higher financial literacy hold a smaller percentage of their portfolio in cash and, thus, a larger share in non-cash investments. This suggests that higher financial literacy is related not only to the extensive margin of stock-holding but also to the intensive margin of portfolio risk-taking.

To study how literacy gaps evolve with investment intensity, we predict the financial literacy using non-cash investment amounts and their interactions with gender and education, controlling for wealth, education, income, and age group. We use the estimated coefficients to construct predicted financial literacy as a function of non-cash investment separately by gender and by degree status, finding significant interaction effects for females and those without a degree. Figure 4 plots the resulting predictions.

At low levels of non-cash investment, there are substantial literacy gaps by gender and by education. As investment increases, the predicted gaps narrow, and at higher levels of investment the profiles for men and women and for degree and non-degree holders converge. These patterns are consistent with declining marginal returns to literacy at higher levels of financial engagement and a direct role for learning-by-doing: individuals who invest more appear to catch up in literacy, especially among groups that start

Figure 4: Predicted Financial Literacy by Non-Cash Investment



(a) By Gender

(b) By Degree

Notes: Figure plots predicted financial literacy scores as a function of estimated non-cash investment amounts. Panel (a) shows predictions by gender, Panel (b) by degree status. Predictions are based on linear regressions of financial literacy on non-cash investment, gender, degree, and their interactions, controlling for wealth, income, age group, and survey wave fixed effects.

from lower initial levels. At the same time, the relationships are estimated in cross-section using an imputed measure of non-cash investment, so they may also reflect selection on unobserved initial literacy or preferences. We therefore treat them as suggestive of learning-by-doing mechanisms and complement them with the instrumental-variable analysis in Section 3.3.

3.3 Estimating Learning-by-Doing

In this subsection, we estimate the effect of stock-market participation on financial literacy, which we interpret as evidence of learning-by-doing. The main empirical challenge is the joint determination of financial literacy and stock ownership. Individuals with higher literacy are more likely to invest in stocks because they face lower informational frictions; conversely, holding stocks may itself increase literacy through experience with financial markets. To address this endogeneity, we exploit variation in recent inheritances as an instrument for stock-market participation and estimate an instrumental-variable ordered-probit model.

Let $FL_i \in \{0, 1, 2, 3, 4\}$ denote the observed financial literacy score for individual i. We model FL_i as arising from an underlying latent literacy:

$$FL_i^* = \gamma\, OwnsStocks_i + X_i'\beta + u_i, \tag{1}$$

where $OwnsStocks_i$ is an indicator for owning stocks, X_i is a vector of controls (gender, degree status, age group, and income group), and u_i is an error term. The observed score is generated by cutpoints $\{\kappa_j\}_{j=0}^4$ such that

$$FL_i = j \quad \text{if} \quad \kappa_{j-1} < FL_i^* \leq \kappa_j, \quad j = 0, 1, 2, 3, 4, \tag{2}$$

with $\kappa_{-1} = -\infty$ and $\kappa_4 = \infty$. We assume u_i is standard normal, so that Equations 1 and 2 define an ordered-probit model. The coefficient γ captures the effect of stock ownership on latent financial literacy, conditional on X_i.

Stock ownership is itself potentially endogenous. We model the latent propensity to hold stocks (Equation 3) and the observed stock-holding (Equation 4) as

$$OwnsStocks_i^* = \delta_1 Z_i + X_i' \delta_2 + v_i, \tag{3}$$

$$OwnsStocks_i = \mathbf{1}\{OwnsStocks_i^* > 0\}, \tag{4}$$

where Z_i is the instrumental variable and v_i is an error term. We allow the errors u_i and v_i to be correlated such that $\text{corr}(u_i, v_i) = \rho$. When $\rho \neq 0$, a single-equation ordered probit that treats $OwnsStocks_i$ as exogenous will generally yield biased estimates of γ, because unobserved determinants of stock-holding and financial literacy are not independent.

The instrument Z_i is a binary indicator for whether the respondent has received an inheritance in the last 12 months that is not associated with the death of a parent or spouse or with a serious accident of a close family member; respondents who report such events are excluded from the baseline sample.[2] This restriction is designed to remove inheritances most likely to come from close relatives who may have directly contributed to the respondent's financial knowledge, thereby increasing the expected social distance between donor and recipient. In our main specification, the estimation sample contains $N = 22{,}742$ individuals, of whom 886 (3.9%) have $Z_i = 1$.[3] Our use of inheritances as a source of exogenous variation in stock-market participation is related to Andersen and Nielsen (2011), who exploit unexpected inheritances in Danish panel data. The exclusion restriction is that, conditional on X_i, these inheritances affect financial literacy only through their impact on stock ownership, either because households inherit stocks directly or because the inheritance relaxes liquidity constraints and induces them to initiate or expand stock-market positions, and not through separate channels that raise financial knowledge independently of holding stocks.

We estimate the endogenous ordered-probit model using full-information maximum likelihood, assuming that (u_i, v_i) are jointly normal.[4] Identification relies on the exclusion of Z_i from the financial literacy equation, together with the functional-form restrictions implied by joint normality and the ordered-probit structure.

[2] Including these observations yields very similar results; see Appendix A.7.

[3] Table A7 reports the distribution of the instrument by investable-asset category. The number of individuals with $Z_i = 1$ is broadly similar across asset groups, although the share is somewhat higher among wealthier households.

[4] This specification is the ordered-outcome analogue of the recursive bivariate probit model in Evans and Schwab (1995), who study Catholic schooling and educational attainment with binary indicators for both treatment and outcome.

Table 3 reports the coefficient estimates from the endogenous ordered-probit specification. In the main specification with gender, education, age, and income controls (column 5), the coefficient on stock ownership in the financial literacy equation is approximately 0.87 ($p < 0.01$), indicating a sizeable positive effect of stockholding on literacy.[5] The estimated correlation between the error terms is negative ($\rho \approx -0.24$). Although we do not reject the null of exogeneity at conventional levels (the p-value for $\rho = 0$ is 0.16), the negative point estimate suggests that, conditional on observables and the instrument, unobserved factors that increase the propensity to hold stocks are associated with slightly lower pre-existing literacy. This is consistent with Figure 2, which shows that a non-trivial share of high-wealth but low-literacy households still participate. One interpretation is that some low-literacy households are drawn into the stock market by traits such as risk tolerance, overconfidence, or peer effects rather than by high initial literacy. Given the absence of strong statistical evidence against exogeneity, we primarily use the endogenous ordered probit to discipline potential endogeneity.[6]

Table 3: Endogenous Ordered Probit – Financial Literacy and Stock Ownership

	Dependent Variable: Financial Literacy Score (Ordered)				
	(1)	(2)	(3)	(4)	(5)
Owns Stocks	1.50***	1.36***	1.31***	0.85**	0.87***
	(0.09)	(0.12)	(0.11)	(0.37)	(0.27)
Female	-0.35***	-0.40***	-0.39***	-0.51***	-0.47***
	(0.03)	(0.03)	(0.03)	(0.06)	(0.04)
Has Degree		0.36***	0.34***	0.51***	0.46***
		(0.03)	(0.03)	(0.06)	(0.04)
Income Controls			Yes		Yes
Age Controls				Yes	Yes
ρ	-0.53	-0.46	-0.46	-0.19	-0.24
$\Pr(\rho = 0)$	0.00	0.00	0.00	0.41	0.16
First-stage Wald χ^2	20.8	14.9	9.5	16.6	10.7
N	27,925	26,899	22,742	26,899	22,742

Notes: Robust standard errors in parentheses. Estimation conducted using Stata's `eoprobit` command with `vce(robust)`. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To give a better interpretation to these results, Table 4 reports the average marginal effects of stockholding on the expected financial literacy score. Moving from not owning stocks to owning stocks raises the expected literacy score by approximately 0.36 points on the 0–4 scale. The effect is present across

[5]The corresponding first-stage, reduced-form, and single-equation ordered-probit estimates are reported in Appendix A.6.

[6]Appendix A.7 shows that these results are robust to alternative definitions of the inheritance instrument and to variations in sample selection.

all subgroups, but its magnitude varies: the effect is larger for women than for men, with a difference of 0.08 ($p = 0.002$), and for respondents without a university degree than for those with a degree, with a difference of 0.08 ($p = 0.003$). Taken together, these patterns indicate that stock-market experience increases financial literacy for all groups, and that the incremental gains are particularly pronounced among individuals who are likely to start from a lower baseline level of financial knowledge.

Table 4: Average Marginal Effect of stock-holding on Expected Financial Literacy Score

Group	**AME**	**Std. Err.**
Overall Sample		
All individuals	0.3574	0.0184
By Gender		
Male	0.3181	0.0140
Female	0.3998	0.0406
By Education (Degree)		
No Degree	0.3872	0.0312
Degree	0.3095	0.0131

Notes: Table reports average marginal effects from an endogenous ordered-probit model. Each effect reflects the average change in expected financial literacy score when stock-holding status changes from 0 to 1, controlling for other covariates and accounting for endogeneity via instrumental variables. Standard errors are obtained by nonparametric bootstrap with 200 replications.

These limitations in family controls and time-variation mean that our IV estimates should be interpreted with some caution, as they may still reflect residual selection on unobservables that is not fully captured by our estimation. A natural next step is to extend the analysis using richer administrative data. In future work, I plan to use Dutch tax-based wealth records linked to household surveys and the whole-population network (see van der Laan et al., 2022) in order to track stock-market participation and financial literacy over time, exploit within-family and within-network variation in participation, and separate peer and family effects from direct learning-by-doing. This type of panel and network structure would allow a sharper identification of the causal effect of stock-market experience on financial literacy and a more detailed characterization of how learning propagates through households and social networks.

4 Model

In this section, we will describe the setup of the finite-horizon partial-equilibrium life-cycle model with endogenous financial literacy accumulation and stochastic asset returns. In brief, households will have the choice between saving in cash and stocks; increasing stock-holdings has an associated utility cost, based on an agent's current level of financial literacy, but has a by-product of increasing the stock of financial literacy in the subsequent period.

4.1 Model Setup

Agents live for T periods, in which they work for the first $T-R$ periods and are retired for the remaining R periods. When working, they supply one unit of labor inelastically and earn a labor income of $z_t w_t$, where z_t is their (stochastic) productivity and w_t is an age-dependent wage that is common to all agents of age t. z_t follows an AR(1) process according to:

$$z_{t+1} = \rho_0^z + \rho_1^z z_t + \varepsilon_{t+1}^z. \tag{5}$$

When agents are retired, they instead receive a fixed transfer, τ_t.

In each period, agents have the choice between saving in two assets: cash (or "money") and stocks. The (gross) interest rate on cash, $R^m = 1 + r^m$, is constant, whereas the return on stocks, $R_t^s = 1 + r_t^s$, is stochastic and is i.i.d. in each period. We will assume that there is a short-selling constraint on stocks; that is, $s_t \geq 0$ for all t. Additionally, there is a borrowing constraint on cash such that, in each period, $m_t \geq \underline{m}$.

Increasing the level of stock-holdings from s_t to s_{t+1} incurs a utility cost, $\kappa(s_{t+1}, s_t, \lambda_t)$, that depends on the level of financial literacy, λ_t, and the reference point (current stock-holdings). We impose an asymmetric cost function for which there is no cost of selling stocks, nor is there a cost of leaving stock-holdings unchanged. This captures the idea that it is mentally less costly choosing which stocks to sell than it is choosing which stocks to buy. To reflect this, we assume that $\kappa(s_{t+1}, s_t, \lambda_t)$ takes the form

$$\kappa(s_{t+1}, s_t, \lambda_t) = \begin{cases} \dfrac{\max\{s_{t+1} - s_t, 0\}}{s_{t+1}\lambda_t}, & \text{if } s_{t+1} > 0, \\ \\ 0, & \text{if } s_{t+1} = 0. \end{cases} \tag{6}$$

Thus, $\kappa(s_{t+1}, s_t, \lambda_t)$ is strictly positive only when $s_{t+1} > s_t$. Conditional on choosing to increase stock-holding, the cost is strictly decreasing in financial literacy.

Agents are endowed with an initial level of financial literacy, denoted by λ_t, which evolves according to the following process:

$$\lambda_{t+1} = \delta_t \lambda_t + \Big(\eta \max\{s_{t+1} - s_t, 0\}^{\psi} + \chi \mathbf{1}\{s_{t+1} > 0\}\Big)\, \lambda_t^{\phi}, \tag{7}$$

where δ_t is an age-specific depreciation rate. The single-period curvature of the learning-by-doing effect as the agent invests a greater amount is controlled by ψ. The parameter η is the return on increasing stock-holdings. The λ^{ϕ} term allows for returns-to-scale on the learning-by-doing effect, affecting the rate of learning for different values of λ_t. When $\phi < 0$, there are decreasing returns-to-scale and the learning is lower for higher literacy; $\phi > 0$ implies increasing returns-to-scale, and $\phi = 0$ implies that the size of learning for a given stock increase is constant. The third term, $\chi\left(\mathbf{1}\{s_{t+1} > 0\}\right)$, measures the effect of having positive stock-holdings on literacy. One could imagine that changing the composition stocks of within a portfolio but leaving the overall amount of investment unchanged could also improve financial literacy. As the model considers stocks to be some composite of holdings, we use this term to allow for unmodeled learning from portfolio adjustments.

The Decision Problem Let us denote by $V_t(s_t, m_t, \lambda_t, z_t, R_t^s)$ the age t value function of agents given the states. The household chooses consumption (c_t), next period stocks (s_{t+1}), and next period cash (m_{t+1}) to maximize the following value function

$$\begin{aligned} & V_t(s_t, m_t, \lambda_t, z_t, R_t^s) = \\ & \qquad \max_{c_t, s_{t+1}, m_{t+1}} u(c_t) - \kappa(s_t, \lambda_t, s_{t+1}) + \beta \mathbb{E}\left[V_{t+1}(s_{t+1}, m_{t+1}, \lambda_{t+1}, z_{t+1}, R_{t+1}^s)\right], \end{aligned} \tag{8}$$

subject to the following constraints:

$$c_t + s_{t+1} + m_{t+1} = z_t w(a) + \tau_t + R_t^s s_t + R^m m_t, \tag{9}$$

$$s_{t+1} \geq 0, \tag{10}$$

$$m_{t+1} \geq \underline{m}. \tag{11}$$

Equation 9 is the standard household budget constraint, and Equations 10 and 11 are borrowing constraints on stocks and cash, respectively. We will assume CRRA utility preferences; that is,

$$u(c_t) = \begin{cases} \frac{c_t^{1-\sigma} - 1}{1-\sigma} & \text{for } \sigma \geq 0, \sigma \neq 1, \\ \ln(c) & \text{if } \sigma = 1. \end{cases} \tag{12}$$

Note that the expectations in the value functions are taken over the realization of the two stochastic processes: individual realizations of productivity, z_{t+1}, and realizations of the stock return, R_{t+1}^s, that are common to all agents. Agents die at the end of time T and, thus, $V_{T+1} = 0$.

4.2 Solving the Model

Let us now summarize how the model is solved computationally, before discussing the calibration and results. A more detailed explanation of the computational solution of the model, including the associated first-order conditions, is provided in Appendix B.

Policy Functions We start by discretizing the AR(1) processes for productivity (Equation 5) using the Tauchen (1986) method, and approximate the stock process by i.i.d. normal distributions. Each of these will take ten discrete values. Stocks and cash take discretized values on a double-exponentiated grid with 40 grid points ranging from 0 to 100; literacy is similarly distributed on a grid from the lowest literacy level, λ^0, to 25, taking 50 discrete values.

Using that $V_{T+1} = 0$ and as there are no bequests in the model, households will optimally consume all resources in the last period, setting $s_{T+1} = 0$ and $m_{T+1} = 0$. Therefore, agents will consume

$$c_T = \tau_T + R^m m_T + R^s_T s_T \quad \Longrightarrow \quad V_T = u(\tau_T + R^m m_T + R^s_T s_T). \tag{13}$$

From the envelope condition, the marginal value function in the terminal period is

$$\frac{\partial V_T}{\partial m_T} = R^m u'(c_T). \tag{14}$$

We will solve the remainder of the periods using the Endogenous Gridpoints Method (EGM) first proposed by Carroll (2006), but more closely following the discrete-continuous EGM adaptation with non-convex adjustment costs by Fella (2014). We will start from the marginal value function of Equation 14 and propagate backwards from period T to 1. As the utility function is separable in consumption, we can invert the first-order condition to obtain an optimal c_t and then back-out the m_t values that justify the asset choices in the following period. Given that we have two asset choice variables, we will solve for the endogenous value of current-period cash, taken s_t as given (on the exogenous grid) and solve conditional on all possible s_{t+1} choices. That is, we treat s_{t+1} as a fixed, discrete choice and then apply a soft-max operator, namely, logit probabilities over the choices of s_{t+1} using the intermediate value functions. The parameter ξ will control the degree of choice dispersion.

Cross-Sectional Distribution We compute the ergodic cross-sectional distribution of household states as the fixed point of the law of motion for the distribution, integrating over the stationary distribution of aggregate stock returns. Conceptually, this corresponds to the cross-sectional distribution obtained after averaging over all possible histories of aggregate returns, so that aggregate shocks enter only through their long-run distribution.

Given an initial cross-sectional distribution of stocks, cash, and financial literacy in period 1, we draw idiosyncratic productivity and aggregate stock returns for the entering cohort from their respective stationary distributions. This implies that households enter the model in an environment in which aggregate risk is already at its long-run distribution. Starting from this initial cross-section, we then use the optimal policy functions and the Markov transition matrices to update the joint distribution period by period from $t = 1$ to $t = T$.

4.3 Calibration

In this subsection, we describe how the model is parametrized and how the exogenously calibrated parameters are determined.

The life cycle consists of $T = 29$ periods, with each period representing two years. Agents are born at age 18, work until age 65 (corresponding to the 64–65 period), and are retired from age 66 onward. The final model period corresponds to ages 74–75, after which agents die, aligning the terminal age with the 75+ category in the FLS data. Because each period spans two years, all model moments that relate to time, for example asset returns and income dynamics, are calibrated at a two-year frequency so that they are consistent with the model's timing structure.

Asset Returns We calibrate stock returns using global equity data from the FTSE All-World Total Return Index over the period from January 2003 to August 2025, which includes reinvested dividends and provides broad exposure to world equity markets. Using a global index is consistent with our partial-equilibrium framework, since UK households are small relative to the global equity market and can reasonably be treated as taking returns as given. We summarize the empirical two-year gross return distribution by fitting a normal distribution that matches the sample mean and standard deviation, which are 20.9 percent and 24.1 percent, respectively, in net terms. For the numerical solution of the model, we discretize this normal approximation into ten return grid points.[7]. We set the two-year return on cash equal to 1.83 percent, or 0.91 percent per annum, in order to match the average annual rate paid on instant-access deposit accounts between January 2011 and August 2025 (Bank of England, 2025).

Household Income We estimate household income dynamics using the measure of "gross regular income" in the WAS. From this data, we obtain two key inputs for the model. First, we estimate the cross-sectional, age-dependent mean household wage in the latest wave of the survey (2020), fitting the following quadratic relationship between age and mean household income:[8]

$$Wage(Age) = -43025.49 + 4488.44 \cdot Age - 50.08 \cdot Age^2. \tag{15}$$

This specification implies an average predicted household wage of approximately £18,420 at age 18, with mean income peaking around age 45 at around £57,500. We normalize the wage rate such that the first-period mean wage is $w_1 = 1$.

[7] The values and associated probabilities are reported in Table B1.

[8] We condition on working-age households and trim the top and bottom 1 percent of the income distribution to remove outliers.

Next, we estimate the idiosyncratic productivity process, z_{it}, for households. We again use the WAS and compute the age-dependent mean income across *all* survey waves, including wave fixed effects that capture nominal wage growth over time. Using the fitted measure of age-dependent wages, $\hat{w}_t$, we define household-specific productivity as

$$\ln(\hat{z}_{it}) = \ln(y_{it}) - \ln(\hat{w}_t), \tag{16}$$

where y_{it} denotes household income.

Because the household-level component of the WAS follows respondents biennially, the two-year gap between interviews coincides with the model's period length. Therefore, one can estimate directly the two-year idiosyncratic productivity process in logs as an AR(1), as in Equation 5. We obtain an estimated persistence of $\hat{\rho}_1^z = 0.75$ (s.e. $= 0.01$), a constant of $\hat{\rho}_0^z = -0.06$ (s.e. $= 0.001$), and a residual standard deviation of $\hat{\sigma}_{\varepsilon^z} = 0.46$. The implied annual persistence is $(\hat{\rho}_1^z)^{1/2} \approx 0.87$, which indicates a high degree of persistence in household-specific productivity, consistent with the range reported by Floden and Lindé (2001), who find annual persistence estimates of 0.91 for the United States and 0.81 for Sweden. We discretize the AR(1) process in (5) using the Tauchen (1986) method with ten grid points spanning plus and minus two unconditional standard deviations of the stationary distribution of $\ln(z_{it})$.

To calibrate the transfer to retirees, we target the replacement rate of UK state pension levels. Cribb et al. (2025) estimate that the state pension replaces 30.2% of average earnings. Using the fitted wage profile in Equation (15) and our normalization of wages to the first-period mean, we obtain an average earnings level of 2.2 in model units. We, therefore, set the per-period transfer to retirees to $\tau = 0.66$ in line with this estimate.

Financial Literacy We calibrate the initial distribution of latent financial literacy, denoted by $\lambda_{t=0}$, to match the empirical distribution of observed literacy scores among households aged 18–24 in the data. In the FLS, the proportions of households with financial literacy scores 0, 1, 2, 3, and 4 are 1.4%, 14.4%, 24.7%, 26.4%, and 33.1%, respectively. We assume that latent financial literacy at model entry takes the form

$$\lambda_{t=0}^i = \lambda^0 \Lambda^i, \quad i = 0, 1, 2, 3, 4, \tag{17}$$

and we choose the parameters λ^0 and $\Lambda > 1$ such that the model-implied shares of agents with each discrete literacy score match the empirical proportions for ages 18–24. Given the calibrated latent levels $\{\lambda_{t=0}^i\}_{i=0}^4$, we define cut-points at the midpoints between adjacent values and use these to partition the continuous λ grid into the five literacy-score categories. Specifically, let

$$\bar{\lambda}_j = \frac{\lambda_0^{j-1} + \lambda_0^j}{2}, \quad j = 1, 2, 3, 4, \tag{18}$$

and define the edges $\{-\infty, \bar{\lambda}_1, \bar{\lambda}_2, \bar{\lambda}_3, \bar{\lambda}_4, \infty\}$. Each agent is then assigned a discrete literacy score $FL_i \in \{0, 1, 2, 3, 4\}$ according to their latent literacy, λ_t; that is, $FL_{i,t} = j$ if $\bar{\lambda}_{j-1} < \lambda_{i,t} \leq \bar{\lambda}_j$, with $\bar{\lambda}_0 = -\infty$ and $\bar{\lambda}_4 = \infty$. These literacy-score categories are held fixed over the life cycle and are used to group agents in the subsequent analysis.

To allow for age-dependent depreciation of financial knowledge, we let δ_t denote the fraction of latent financial literacy that survives from period t to period $t+1$. We parameterize the sequence $\{\delta_t\}_{t=1}^{T}$ as linearly declining in t, starting from 1 in the first period and reaching a terminal value $\underline{\delta} \in (0, 1)$ in the last period. This specification implies that older households experience faster depreciation of financial knowledge than younger households.

Initial Distributions We choose three mass points for initial cash holdings, $\{0.1, 0.6, 5\}$, with probabilities $\{0.45, 0.50, 0.05\}$ in order to approximate the FLS distribution of investable assets for 18–24 year olds. In the FLS, around 2% of young households report more than £50,000 in investable assets, about 4% report £20,000–£50,000, and the vast majority report less than £20,000. This motivates concentrating almost all of the mass on low and moderate initial cash levels and assigning only a small share to the high-wealth point. We initialize income productivity according to the stationary Markov distribution.

4.3.1 Calibration Results

We now summarize the externally calibrated parameters before turning to the parameters that are chosen internally to match selected moments. Table 5 summarizes the externally calibrated parameters as described above. Internal parameters are chosen to ensure that the model matches key features of the joint distribution of wealth, stock-market participation, and financial literacy. Table 6 reports these parameters; Table 7 reports the corresponding moments.

We use the discount factor β to target the mass of households with zero investable assets in the FLS data. The calibrated two-year value of $\beta = 0.568$ implies a quarterly discount factor of approximately $\beta^{1/8} \approx 0.93$, which is similar in magnitude to values used in recent heterogeneous-agent macroeconomic models.[9] Although we do not target marginal propensities directly, the calibrated model implies an average two-year marginal propensity to consume (MPC) of about 0.36. This is lower than the two-year horizon MPC of roughly 0.7 estimated by Fagereng et al. (2021), which is plausible given that our calibration is primarily disciplined by wealth and participation moments rather than short-run consumption responses. We, therefore, view the implied MPC as a relatively conservative estimate that remains compatible with the broader empirical evidence and sufficient for the quantitative exercises that follow.

[9]For example, Auclert et al. (2023) estimate an average quarterly discount factor of about 0.95 when targeting quarterly MPCs of 0.25.

Table 5: Model Parameters – External Calibration

	Description	**Value**	**Target / Source**
A. Demographics			
T	Number of life-cycle periods	29	Ages 18–75 in two-year steps
R	Number of retirement periods	5	Ages 66–75 in two-year steps
B. Returns			
r^m	Cash return (two-year)	0.0183	Average deposit rate, 2011–2025
$\mathbb{E}[r^s]$	Mean equity return (two-year)	0.2090	FTSE All-World, 2003–2025
σ^s	Std. dev. of equity returns	0.2410	FTSE All-World, 2003–2025
C. Income			
ρ_0^z	Constant in log-productivity	-0.06	WAS household panel
ρ_1^z	Persistence of log-productivity	0.75	WAS household panel
σ_{ε^z}	Shock std. dev.	0.46	WAS household panel
D. Other			
$\underline{m}$	Borrowing limit	0	No borrowing
τ	Retiree transfer	0.66	30% replacement rate
ξ	Taste shock	0.01	Externally imposed

Notes: External parameters are calibrated to empirical data on income and returns, as discussed in Section 4.3.

Table 6: Model Parameters, Internal Calibration

	Description	**Value**
A. Preferences		
β	Discount factor	0.568
σ	CRRA coefficient	3.250
γ	Portfolio taste weight	1.000
B. Financial Literacy Accumulation		
χ	Literacy return (holding)	58.000
η	Literacy return (increase)	71.000
ψ	Stock-increase curvature	0.065
ϕ	Learning curvature	-1.630
$\underline{\delta}$	Final depreciation rate	0.981
C. Initial Literacy		
λ^0	Initial literacy (lowest group)	2.500
Λ	Literacy scaling factor	1.660

Notes: Internal parameters are calibrated to match key empirical moments of stock-market participation, portfolio composition, and financial literacy over the life cycle.

The coefficient of relative risk aversion σ is primarily disciplined by the aggregate cash-to-stock ratio reported in Table 7. The calibrated value $\sigma = 3.25$ is moderate by the standards of the life-cycle portfolio literature and is well below the very high levels often required in models without financial-literacy frictions to jointly match limited participation and wealth.[10] Our framework can replicate participation and portfolio patterns with substantially lower risk aversion because part of the reluctance to hold stocks is attributed to financial-literacy frictions rather than to preferences alone.

Table 7: Model Performance – Targeted Moments

	Model	**Target**	**Source**
A. Stock-Market Participation			
Overall participation rate	24%	22%	FLS – 2022
Participation rate (Under age 25)	7%	7%	FLS – 2022
Participation rate (Retirees)	34%	28%	FLS – 2022
B. Wealth Distribution			
Households with zero financial assets	11%	12%	FLS – 2022
Cash-to-stock asset ratio	7.48	9.88	Table 1
C. Financial Literacy Ratios			
Stockholders vs. non-stockholders	1.67	1.22	FLS – 2022
75th-to-25th percentile of stock-holdings	1.04	1.07	FLS – 2022
End-of-life vs. retirement period	0.94	0.93	FLS – 2022
Ages 35–44 vs. Ages 18–24	1.01	1.30	FLS – 2022

Notes: Table compares model-generated targeted moments to empirical values from the Financial Literacy Survey (FLS, 2022) and the Wealth and Assets Survey (WAS, 2020). "Model" values represent simulated outcomes under the calibrated parameterization. All percentages refer to household shares unless noted otherwise.

The remaining parameters $(\chi, \eta, \psi, \phi, \underline{\delta}, \lambda^0, \Lambda)$ are chosen jointly so that the model reproduces the level and life-cycle profile of stock-market participation, the cash-to-stock asset ratio, and the differences in financial literacy between stockholders and non-stockholders, between households with high and low stock-holdings, and across age groups, as summarized in Table 7.[11] One can notice that the model underestimates both the financial literacy of non–stockholders and the growth in average literacy between ages 18–24 and 35–44. In practice, even individuals who do not participate in the stock market are likely to accumulate financial knowledge over time through interactions with other financial products, for example when purchasing a home, taking on mortgages or other loans, or managing non-equity savings products, that are not explicitly modeled in this framework.

[10] In such models, values of σ around 8–10 or higher are common: for example, a baseline of 10 in Cocco et al. (2005) and estimates in the range 11–14 in Fagereng et al. (2017).

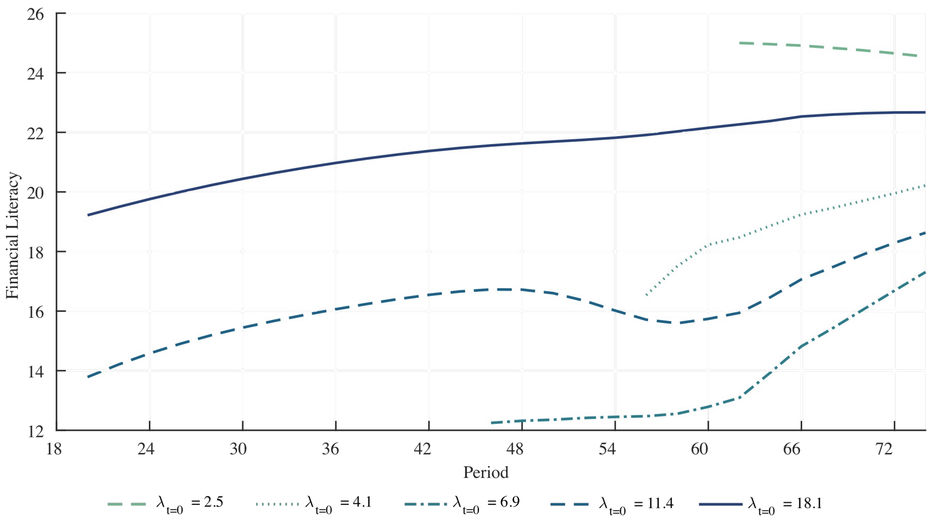
[11] Table B2 reports the cut-points of grouping of financial literacy score, given λ^0 and Λ.

5 Results

We now turn to the main quantitative implications of the model for stock-market participation, portfolio allocation, and the role of learning-by-doing in closing early-life literacy gaps.

Figure 5 examines how learning-by-doing affects literacy gaps across cohorts. The figure plots the evolution of average latent literacy for the five initial cohorts, *conditional* on holding stocks, with the solid blue line corresponding to the highest-literacy cohort. Conditional on participation, literacy differences between cohorts narrow over the life cycle. For instance, the second-highest cohort ($\lambda_{t=0} = 11.4$) starts with latent literacy of about 63% of the highest group, but among stockholders this ratio rises to roughly 77% at retirement and 84% by the end of life. Lower-literacy cohorts display a similar pattern: while only a small share of the lowest group (around 3%) ever enter the stock market, those who do so (after accumulating sufficient cash wealth) large increases in literacy. Entry for these low-literacy cohorts occurs relatively late in the life cycle, which highlights the importance of initial literacy for extensive-margin participation: high-literacy households are willing to hold stocks even when liquid wealth is modest, whereas low-literacy households typically delay entry until they have built up sizable cash balances. Overall, conditional on stock-holding, differences in financial literacy across cohorts shrink markedly over time, in contrast with the persistent gaps that remain among non-stockholders.

Figure 5: Financial Literacy of Cohorts, Conditional on stock-holding

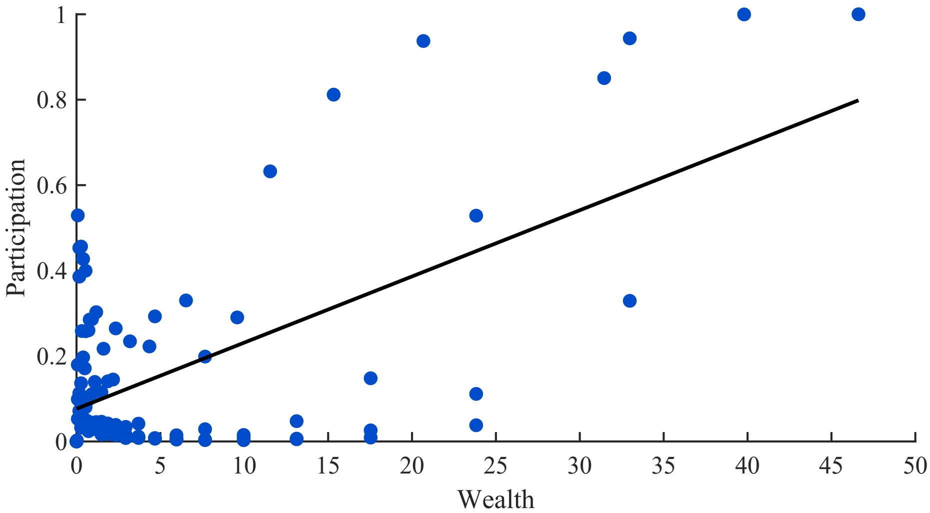


Notes: This figure shows, for each initial cohort of financial literacy, the average financial literacy level *conditional* on holding stocks in that period of the model. This is the average across wealth, productivity, and stock returns in the distribution.

One of the key distinctions between monetary participation costs and the non-monetary literacy frictions in our framework is the implied relationship between wealth and stock-market participation. In standard models with purely monetary costs, participation is almost mechanically increasing in wealth, whereas the data show a much weaker link, with substantial participation among low-wealth but high-literacy households and non-trivial non-participation among high-wealth but low-literacy households (see, for example, Figure 2).

We now assess this fit in the model. Figure 6 plots a binned scatter of participation rates against wealth across all periods, revealing a strong but far from perfect relationship. The correlation between stock-holdings and total wealth is 0.59, indicating that richer households are more likely to participate and hold more stocks, but that wealth alone does not fully determine participation. This imperfect correlation arises because the effective cost of entering the stock market declines with financial literacy, not purely with wealth. High-literacy, low-wealth households face a low literacy cost and, therefore, begin participating at relatively modest wealth levels, while low-literacy households must accumulate substantial cash balances before it becomes optimal to pay the literacy cost of entry.

Figure 6: Model Wealth and Participation Rates



Notes: Figure plots a binned scatter (100 bins) of wealth against stock-market participation in the model, pooling all periods. The correlation between participation and wealth is 0.59.

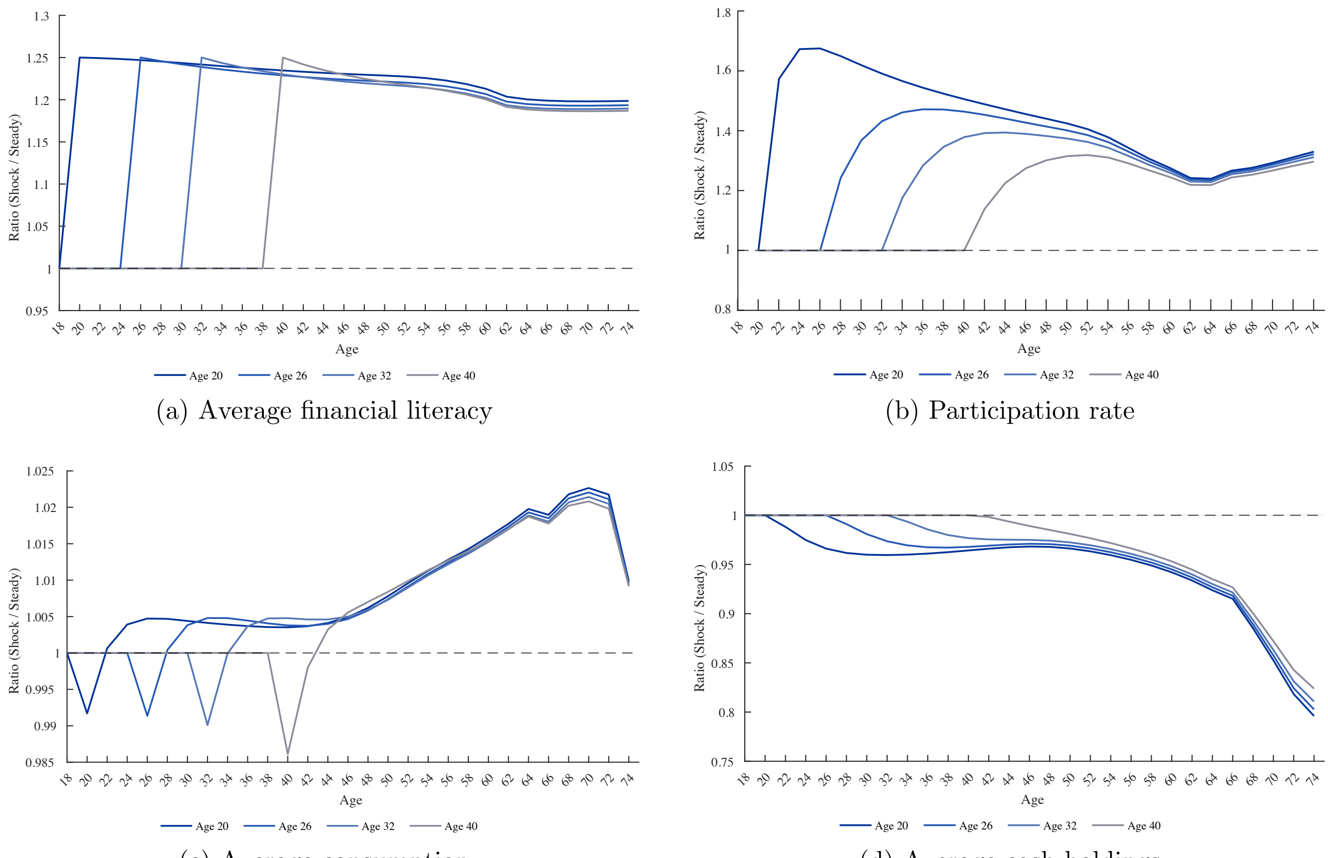
6 Policy Analysis

We use the quantitative model to compare the effectiveness of alternative policies aimed at increasing financial literacy and stock-market participation. First, we study the timing of financial literacy programs, asking whether it is more effective to target individuals early in life or closer to retirement. Second, we compare equal-sized transfers delivered in cash versus in the form of stock-market assets, and evaluate which type of transfer generates larger welfare gains for households.

We first consider a 25% increase in latent financial literacy, interpreted as a financial education program, delivered at different ages (20, 26, 32, and 40). Figure 7 plots the ratio of key moments under the policy to the baseline. Although the boost is identical, panel (a) shows that average literacy ends up slightly but persistently higher when the program is delivered at age 20, reflecting stronger participation responses and more time for learning-by-doing; panel (b) similarly shows the largest proportional participation gains for younger cohorts. Retirement consumption levels are very similar across intervention ages (panel (c)), though older recipients experience a somewhat sharper short-run consumption adjustment as they reoptimize. Cash holdings fall in all cases (panel (d)), with earlier interventions leaving households at retirement with marginally lower cash balances and a slightly higher stock share.

Quantitatively, the differences between these shocks in the last working period before retirement are modest (see Table B3): relative to an otherwise identical boost at age 40, a program at age 20 raises pre-retirement participation by about 1 percentage point and latent literacy by roughly 1%. This is consistent with the visual impression from Figure 7, where the policy paths for different intervention ages are close to one another. The results, therefore, suggest that, within this framework, the timing of a given literacy intervention is of second-order importance quantitatively, but earlier programs have a mild advantage because additional years of stock-market exposure amplify the gains from financial education through learning-by-doing.

Figure 7: Financial Literacy Shocks by Age: Ratio of Post-Shock to Steady State



(a) Average financial literacy

(b) Participation rate

(c) Average consumption

(d) Average cash holdings

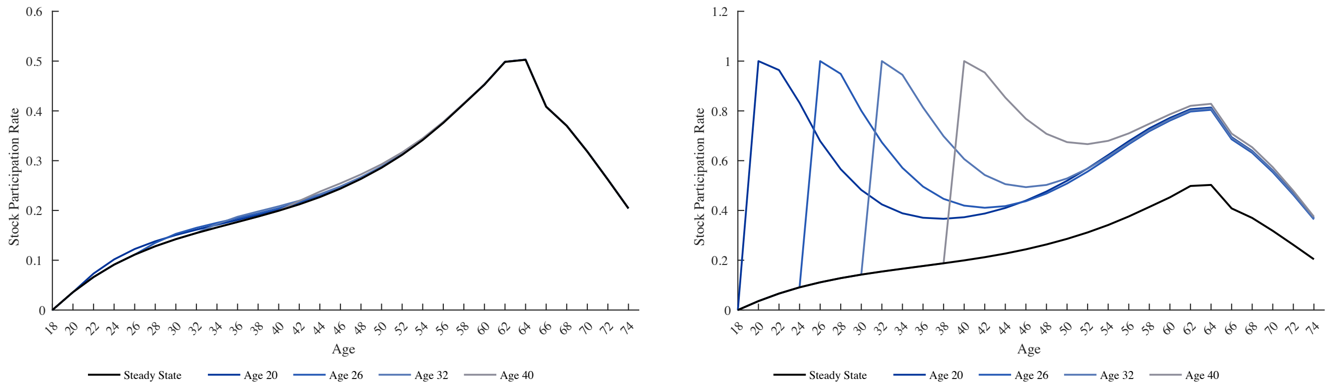
Notes: This figure shows the ratio of shock-to-steady-state moments across for the financial literacy boosts at ages 20, 26, 32, 40.

We now compare the implications of transferring 0.25 units of either cash or stock to households at different points in the life cycle. Two main messages emerge. First, cash transfers of this size have almost no effect on long-run participation: they primarily relax short-run liquidity constraints and are largely consumed. Second, stock transfers have a persistent and sizeable effect on long-run participation, wealth, and consumption due to the learning-by-doing effect loosening literacy frictions and positive long-run returns generating additional wealth.

Figure 8 illustrates the participation response. Panel (a) shows that cash transfers induce only a very modest increase in stock-market entry, mainly by bringing forward participation for households that were already close to their entry threshold; by the last working period, the participation rate is higher by only about 0.1 percentage points and average latent literacy by roughly 0.2% relative to the no-transfer benchmark, and the cash transfer has been almost entirely consumed (see Table B4). In contrast, panel (b) shows that stock transfers mechanically move recipients into the market in the period of the transfer and, even after some households subsequently disinvest and exit, participation remains persistently higher. In the pre-retirement period, participation is about 30 percentage points above the baseline, average literacy is roughly 40% higher, and both wealth and consumption are 4–5% above the no-transfer economy.

The timing of stock transfers matters, but only moderately. Comparing a stock transfer at age 20 with the same transfer at age 40, the younger cohort enters retirement with stock-holdings approximately 3% higher, latent literacy about 2% higher, and consumption about 0.5% higher. These differences are quantitatively modest but economically intuitive: when the transfer is made earlier, households spend more years in the market, which amplifies the effect through learning-by-doing and cumulative portfolio re-optimization. Overall, the results imply that, for a given fiscal cost, in-kind transfers in the form of equity are far more effective than cash at raising long-run participation, literacy, and retirement resources, and that targeting younger households yields slightly higher returns on such interventions.

Figure 8: Cash vs. Stock Transfer by Age: Participation Rates



(a) Cash transfer

(b) Stock transfer

Notes: The figure shows the life-cycle participation rates following cash and stock transfers at ages 20,26, 32, and 40.

7 Aggregate Shocks in an Economy with Higher Financial Literacy

We now examine how aggregate dynamics change in an economy with higher financial literacy and, consequently, greater stock-market participation and a higher allocation of assets towards stocks. Specifically, we consider a counterfactual in which agents are born with latent financial literacy that is 25% higher than in the benchmark steady state. This thought experiment can be interpreted as the long-run outcome of large-scale financial education initiatives in schools, or of early-life programs that expose young individuals to stock-market participation through simulated trading environments. Starting from this higher-literacy steady state, we compare the response of the economy to two types of aggregate shocks: (i) a negative income shock that affects all households and (ii) a financial shock in which aggregate stock returns are temporarily negative. After the one-time shock, we plot the transition for the 30 following periods (equivalent to 60 years). Each period, agents of age T die and a new mass of agents is born to replace this mass.

7.1 Shock to Household Income

As the model is partial equilibrium and households supply labor inelastically, we introduce an aggregate labor-income shock by shifting downward the idiosyncratic productivity component z_t of all households. This provides an exogenous shock to earnings with persistence governed by the calibrated income process, while ruling out general-equilibrium feedback through wages or prices. One can interpret this as a sharp macroeconomic downturn, for example a severe recession or pandemic episode that depresses earnings broadly.[12]

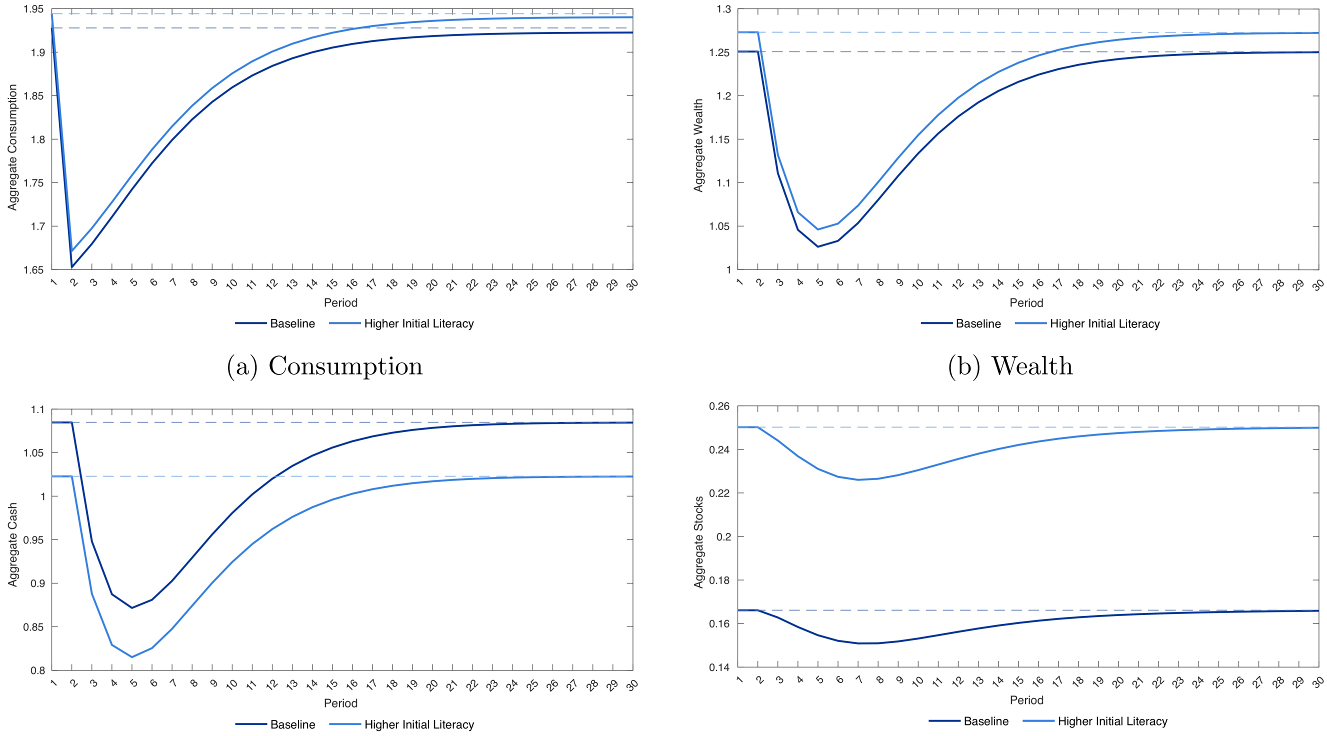
More specifically, in the period of the shock, we move each household's productivity down by one grid point (except for those already at the lowest grid point), leaving the transition matrix for z_t unchanged thereafter. This produces an immediate fall of approximately 25% in average labor income, followed by a gradual recovery that brings income back to about 99% of its long-run level after roughly 16 periods. To emulate a prolonged recession, new agents are born with a productivity distribution that matches the aggregate in that given period. Figure 9 plots the transition of aggregate moments following the income shock in the baseline and higher-literacy economies.

As higher literacy raises saving and portfolio returns in the steady state, both consumption and wealth start from higher levels before the shock and the troughs of consumption and wealth are higher when the shock hits. The subsequent recovery of each economy toward its own steady state is similar in speed, although the higher-literacy economy crosses the baseline equilibrium after roughly 16 periods and remains above thereafter. Thus, in this partial-equilibrium environment, higher literacy does not materially accelerate the rate at which the economy recovers from an income shock, but it does mitigate the level decline in consumption and wealth.[13] Panels (c) and (d) further show that cash holdings fall

[12]In a general-equilibrium setting, such a downturn would also affect wages, interest rates, and labor-supply decisions. In the present partial-equilibrium framework, we have abstracted from these feedback effects and treat the income shock as exogenous. Extending the analysis to incorporate these additional channels is left for future research.

[13]Melcangi and Sterk (2025) show that higher participation can strengthen the transmission of monetary policy, so in general equilibrium, with endogenous interest rates and policy interventions, higher literacy could also affect the speed of recovery.

Figure 9: Income Shock - Baseline vs Higher Initial Literacy: Aggregate Moments



(a) Consumption

(b) Wealth

(c) Cash

(d) Stocks

Notes: The figure plots the levels of (a) consumption, (b) wealth, (c) cash, and (d) stocks following a one-off fall in productivity in which all agents have their labor productivity, z_t, reduced by one grid point. The economy is then simulated for 30 subsequent periods. The dark blue line shows the baseline economy, calibrated in Section 4.3; the light blue line shows an economy in which agents born in period 1 have 25% higher initial financial literacy.

by a similar amount across economies, while stock positions decline more in the higher-literacy case, so larger pre-shock stock-holdings serve as a buffer that helps smooth consumption during the shock.

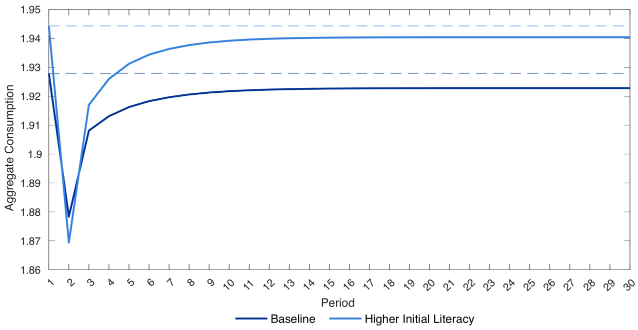
7.2 Shock to Financial Returns

We now consider the effects of a stock-market shock in the two economies. Specifically, we impose a one-off shock in which the stock return takes the lowest value in our discrete grid, corresponding to a 27.5% fall in stock values.[14] The shock hits once, after which the stock return is assumed to follow its stationary distribution. We start from the pre-shock ergodic distribution, apply the one-period shock, and then let the cross-sectional distribution evolve where we integrate over the many paths of stock returns; this gives the expected transition path over the many possible return values. Figure 10 plots the transitions of these economies.

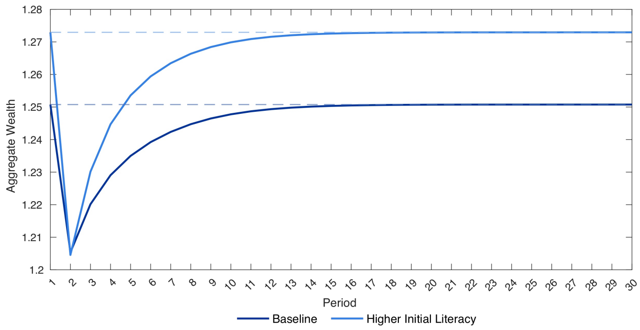
Higher literacy and portfolio allocation towards stocks means that the high-literacy economy is more exposed to a negative stock-market realization. Consistent with this, the drop in consumption is larger,

[14]Under our normal approximation, this realization would occur with probability 2.5%.

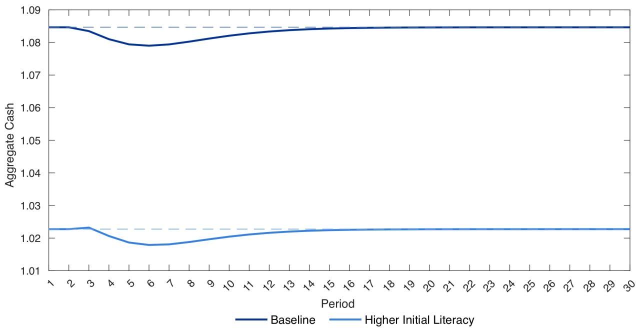
Figure 10: Return Shock - Baseline vs Higher Initial Literacy: Aggregate Moments



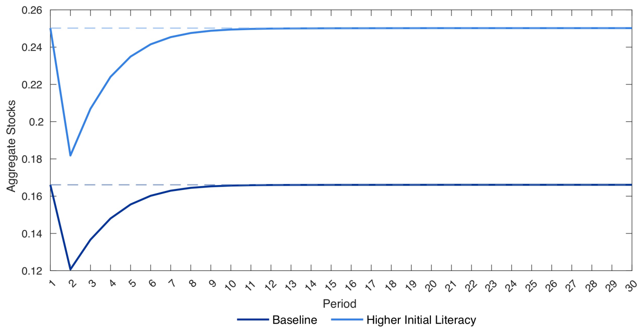
(a) Consumption



(b) Wealth



(c) Cash



(d) Stocks

Notes: The figure plots the levels of (a) consumption, (b) wealth, (c) cash, and (d) stocks following a one-off negative shock to returns (-27.3%). The economy is then simulated for 30 subsequent periods. The dark blue line shows the baseline economy, calibrated in Section 4.3; the light blue line shows an economy in which agents born in period 1 have 25% higher initial financial literacy.

both in levels and in percentage terms. Aggregate wealth in the two economies reaches a similar trough, but the high-literacy economy recovers much faster: its wealth path crosses the baseline level after about four periods, whereas it takes roughly fourteen periods for the baseline economy to reach the same level. Thus, higher literacy increases vulnerability to rare asset price crashes, yet it also speeds up the rebuilding of wealth once the shock has occurred.

Taken together, these two aggregate shocks highlight an important trade-off associated with higher stock-market participation. Higher financial literacy brings more households into the stock market, raising average wealth and consumption and cushioning income shocks, so that downturns in earnings translate into smaller declines in consumption levels. At the same time, greater equity exposure makes the economy more vulnerable to adverse return realizations, leading to sharper drops in wealth and consumption when asset prices fall, even though wealth rebuilds more quickly in the high-literacy economy once the shock has occurred.

8 Conclusion

In this paper, we have studied how financial literacy frictions shape both the extensive and intensive margins of stock-market participation. Using new evidence from the FCA Financial Lives Survey and a life-cycle model with endogenous financial literacy, we show that large early-life gaps in literacy by gender and education narrow among households that invest in non-cash assets, consistent with learning-by-doing through stock-market participation. Modeling literacy as a non-monetary friction weakens the wealth–participation gradient in a way that matches the data, with some high-literacy, low-wealth households holding stocks and some low-literacy, high-wealth households remaining out.

Empirically, we document sizable literacy gaps between men and women and between those with and without a university degree, and we show that these gaps shrink as non-cash holdings rise. Among households with more than £10,000 in investable assets but held entirely in cash, the predicted literacy gap between men and women is around 0.3 correct answers; this gradually fades as invested assets rise to £250,000. Additionally, we see that stock-market participation increases sharply with the number of correct literacy answers, while the share of the portfolio held in cash falls. Even among households with more than £250,000 in assets, low-literacy households keep a large majority of their portfolio in cash, whereas high-literacy households hold substantially more in risky assets.

We embed these patterns in a partial-equilibrium life-cycle model in which financial literacy evolves via learning-by-doing. Calibrated to UK data, the model replicates key features of the joint distribution of wealth, literacy, and participation, including substantial cash balances and limited equity exposure among many high-wealth households. Literacy acts as a non-monetary participation friction: low-literacy households rationally stay out despite high wealth, while high-literacy but low-wealth households enter due to relatively lower costs. As a result, the model delivers an imperfect correlation between wealth and participation of about 0.59.

We use the model to compare equal-sized cash and stock transfers and to study aggregate shocks. Cash transfers have negligible effects on participation, mainly relaxing liquidity constraints for households that would have entered later anyway. Stock transfers, by contrast, produce sizable and persistent increases in participation, literacy, and consumption, as initial exposure to equities feeds back through learning-by-doing. Higher literacy and participation raise long-run wealth and consumption and soften the impact of income shocks, but they also make households more exposed to rare asset-price crashes, which generate larger short-run drops in consumption even as wealth subsequently recovers more quickly.

Overall, the analysis highlights the importance of non-monetary literacy frictions and learning-by-doing for understanding who participates in stock markets, how portfolios are allocated, and how households respond to shocks and policy interventions. In future work, I will use richer administrative and panel data to sharpen causal estimates of learning-by-doing and embed this framework in general equilibrium to study the interaction between financial literacy, asset markets, and the broader macroeconomy.

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A Empirical Appendix

A.1 Financial Literacy Elicitation Questions

The FLS includes the following items adapted from the "Big Three" financial literacy questions introduced by Lusardi and Mitchell (2008):

Q1. Suppose you put £100 into a savings account with a guaranteed interest rate of 2% per year (with no fees or tax to pay). How much would be in the account at the end of the first year, once the interest payment is made? (*Numeric response*)

Q2. And how much would be in the account at the end of five years (remembering that there are no fees or tax deductions)?

a. More than £110

b. Exactly £110

c. Less than £110

d. It is impossible to tell from the information given

e. Don't know

Q3. If the inflation rate is 5% and the interest rate you get on your savings is 3%, will your savings have more, less, or the same amount of buying power in a year's time?

a. More

b. The same

c. Less

d. Don't know

Q4. Is the following statement true or false? "Buying shares in a single company usually provides a safer return than buying shares in a range of companies."

a. True

b. False

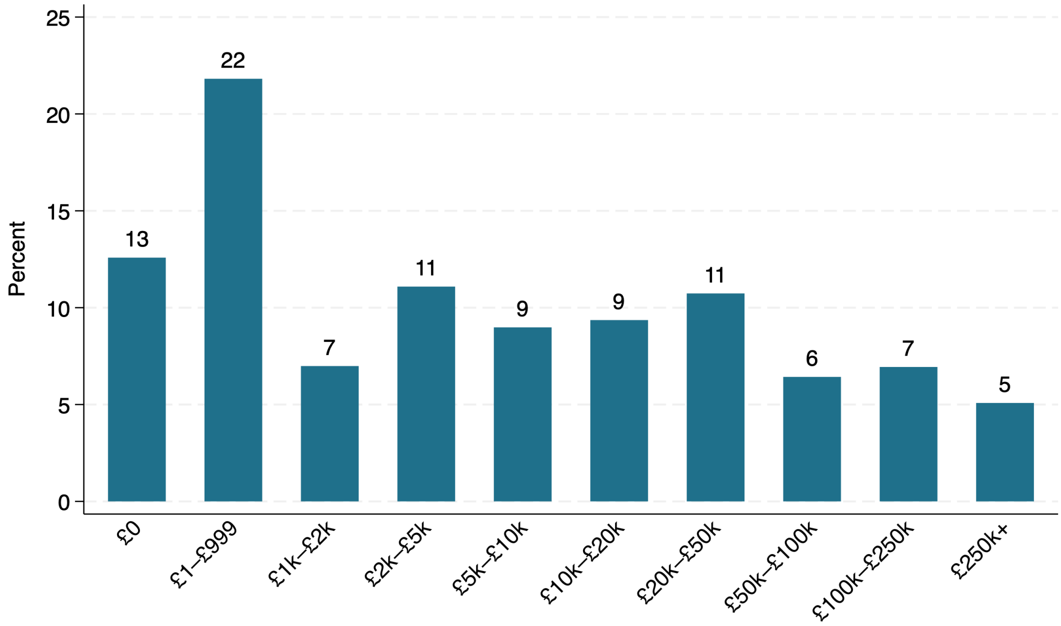
c. Don't know

A.2 Distribution of Investable Assets

A.3 Construction of Non-Cash Investment Measure

Because the Financial Lives Survey (FLS) does not directly record the monetary value of households' non-cash investments, we approximate this using the available categorical data. Specifically, we combine

Figure A1: Distribution of Investable Assets



Notes: The figure reports the distribution of households by self-reported level of investable assets corresponding to the categories on the x-axis.

(i) the midpoint of each household's reported *investable asset* bracket with (ii) the midpoint of their reported *propensity to invest* category (i.e., the share of savings held in cash versus non-cash assets). The highest investable asset category is truncated at £250,000 to avoid over-weighting of open-ended responses. This procedure yields a continuous proxy for non-cash investment amounts that preserves ordinal variation across both wealth and portfolio composition, maintaining internal consistency with the categorical structure of the data.

Table A1: Investable Asset Categories and Assigned Midpoints

Code	**Category Description**	**Assigned Midpoint (£)**
1	£0	0
2	£1–£999	500
3	£1,000–£1,999	1,500
4	£2,000–£4,999	3,500
5	£5,000–£9,999	7,500
6	£10,000–£19,999	15,000
7	£20,000–£49,999	35,000
8	£50,000–£99,999	75,000
9	£100,000–£249,999	175,000
10	£250,000 or more (truncated)	250,000

Notes: This table reports the investable asset categories provided in the Financial Lives Survey (FLS) and the corresponding midpoints used to construct continuous approximations of investable wealth. The upper open-ended category is truncated at £250,000 to prevent over-weighting of extreme values.

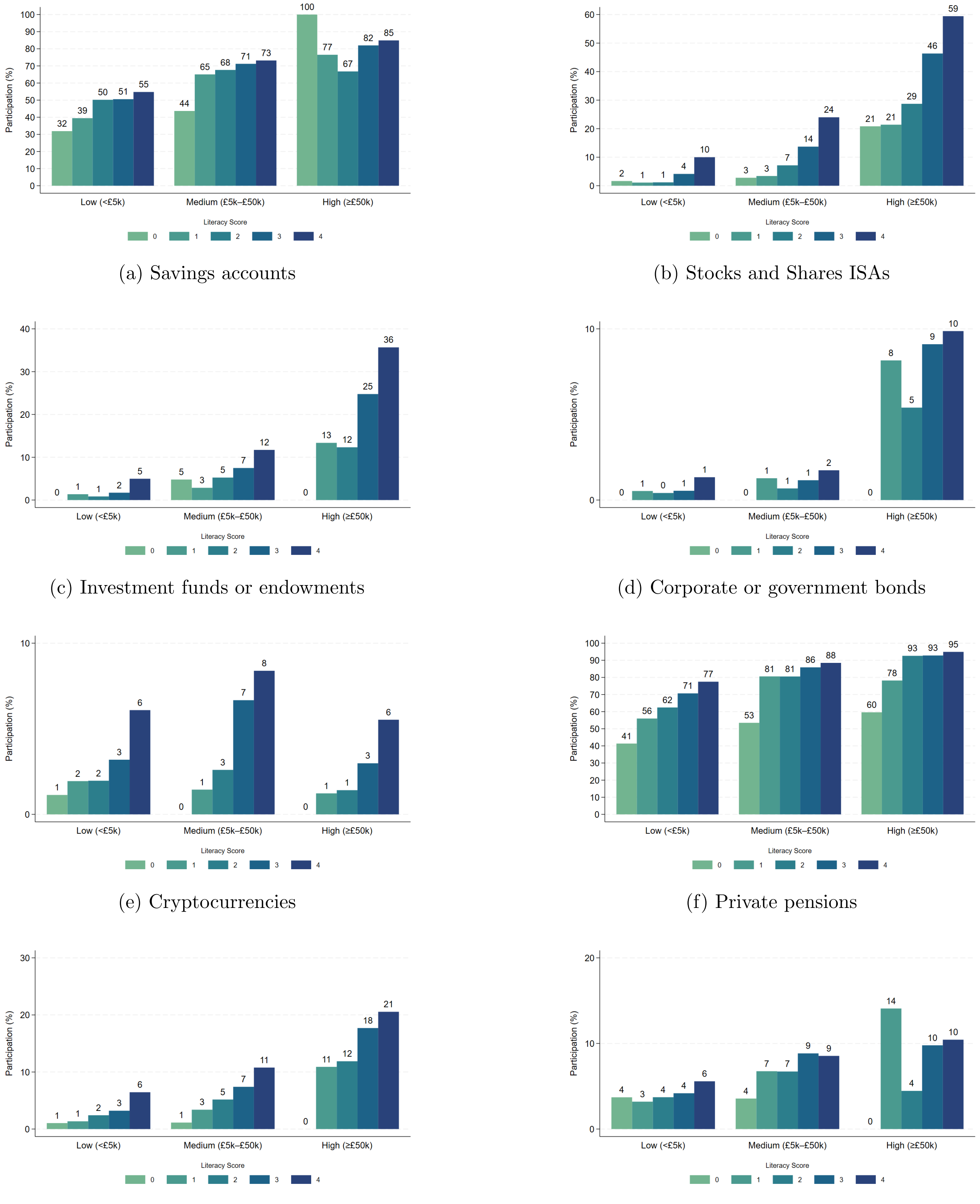
Table A2: Propensity to Invest Categories and Assigned Midpoints

Code	Category Description	Assigned Cash Share (%)
1	All in cash	100.0
2	Mostly in cash (75%+ held in cash)	87.5
3	Mixed portfolio (26–74% held in cash)	50.0
4	Mostly or fully invested (0–25% held in cash)	12.5

Notes: This table shows the categorical breakdown of the *propensity to invest* variable for households with at least £10,000 in investable assets. The assigned midpoint reflects the approximate share of assets held in cash, with the complement used to estimate the non-cash (investment) share when constructing continuous investment values.

A.4 Participation Rates by Product Type

Figure A2: Participation by Investable Assets and Financial Literacy Score, by Product Type



(a) Savings accounts

(b) Stocks and Shares ISAs

(c) Investment funds or endowments

(d) Corporate or government bonds

(e) Cryptocurrencies

(f) Private pensions

(g) Property investments

(h) Other real investments*

Notes: Each panel plots the participation rate in a specific financial product by categories of investable assets and financial literacy score. The three investable asset categories are defined as: *low* (under £5,000), *medium* (£5,000–£49,999), and *high* (above £50,000). *"Other real investments" includes, for example, wine, art, jewelry, antiques, vintage cars, and other collectibles.

Table A3 shows how holding of other asset classes varies by stock-ownership status; we see that those who hold stocks are also more likely to hold other asset types.

Table A3: Asset Holdings by Stock-Market Participation Status

	% Holding Product		
	No Stocks	**Has Stocks**	**Diff (pp)**
Savings account	54.8	77.1	22.3***
Corporate/government bonds	1.0	8.3	7.4***
Cryptocurrency	2.0	6.9	4.9***
Investment property	5.0	16.7	11.7***
Other real assets	3.5	10.6	7.1***

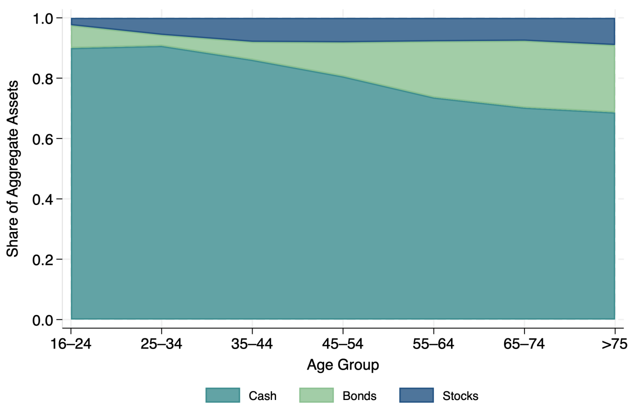
Values are percentages. Differences reported in percentage points.

*** $p < 0.01$.

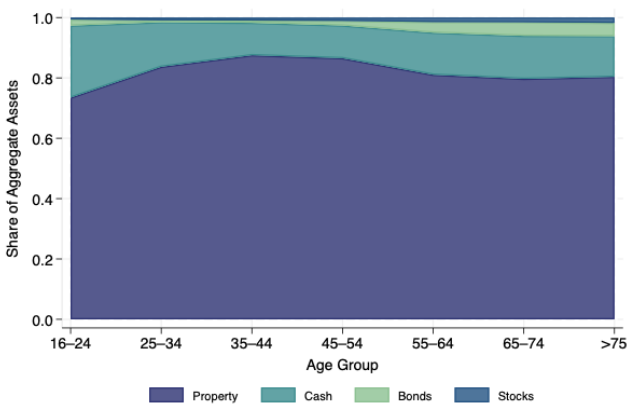
A.5 Portfolio Shares by Age and Asset Type

Figure A3 shows the aggregate portfolio shares by age group as reported in the Wealth and Asset Survey. Panel A3a focuses on financial assets, whereas Panel A3b adds net property wealth. Property accounts for the bulk of total wealth, close to 80% in the aggregate. Conditional on financial assets, Bonds also account for a non-trivial share of aggregate financial portfolios, even though they are held by relatively few households, as shown in Table 1. Portfolio shares are remarkably stable across the life cycle: the equity share rises up to ages 35–44 and then remains fairly flat, while the bond share increases gradually with age, largely offsetting declines in cash but leaving the equity share roughly unchanged.

Figure A3: Aggregate Portfolio Shares by Age, With and Without Property



(a) Excluding property



(b) Including property

A.6 Auxiliary IV Regressions

This appendix reports the auxiliary regressions corresponding to the endogenous ordered-probit specification in Section 3.3. All specifications use the same set of controls X_i (gender, degree status, age group, and income group), are estimated on the same sample as the main IV model, and employ survey weights and robust standard errors.

A.6.1 First-Stage Probit

The first-stage equation relates the stock-holding indicator $OwnsStocks_i$ to the inheritance instrument Z_i and controls X_i:

$$\Pr\big(OwnsStocks_i = 1 \mid Z_i, X_i\big) = \Phi\big(\alpha_0 + \alpha_1 Z_i + X_i'\alpha_2\big), \tag{19}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. Table A4 reports the probit estimates.

Table A4: First-Stage Probit – stock-holding on Inheritance Instrument

	(1)
	$OwnsStocks_i$
Inheritance Z_i	0.223***
	(0.070)
Female	-0.306***
	(0.024)
Has degree	0.299***
	(0.023)
Income controls	Yes
Age controls	Yes
N	22,595

Robust standard errors in parentheses.

Baseline categories are male, no degree, ages 18–24, and income group 1.

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

A.6.2 Reduced-Form Ordered Probit

The reduced-form relationship between the inheritance instrument and financial literacy is

$$FL_i^* = \pi_0 + \pi_1 Z_i + X_i'\pi_2 + \varepsilon_i, \tag{20}$$

with the observed ordered outcome generated by thresholds $\{\kappa_j\}_{j=0}^{4}$ as in

$$FL_i = j \quad \text{if} \quad \kappa_{j-1} < FL_i^* \leq \kappa_j, \quad j = 0, 1, 2, 3, 4, \tag{21}$$

and $\kappa_{-1} = -\infty$, $\kappa_4 = \infty$. Table A5 reports the ordered-probit estimates.

Table A5: Reduced-Form Ordered Probit – Financial Literacy on Inheritance Instrument

	(1)
	FL_i
Inheritance Z_i	0.293***
	(0.067)
Female	-0.544***
	(0.021)
Has degree	0.528***
	(0.020)
Income controls	Yes
Age controls	Yes
N	22,599

Robust standard errors in parentheses.

Baseline categories are male, no degree, ages 18–24, and income group 1.

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

A.6.3 Single-Equation Ordered Probit

For comparison, we also estimate a single-equation ordered-probit model that treats stock-holding as exogenous:

$$FL_i^* = \gamma^{\text{SE}} OwnsStocks_i + X_i' \beta^{\text{SE}} + u_i, \tag{22}$$

with FL_i linked to FL_i^* via the same threshold structure as in (21). Table A6 reports the corresponding estimates.

Table A6: Single-Equation Ordered Probit – Financial Literacy on stock-holding

	(1)
	FL_i
Owns Stocks	0.478***
	(0.024)
Female	-0.513***
	(0.021)
Has degree	0.500***
	(0.020)
Income controls	Yes
Age controls	Yes
N	22,595

Robust standard errors in parentheses.

Baseline categories are male, no degree, ages 18–24, and income group 1.

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

A.7 IV Robustness Checks

This subsection reports several robustness checks for the endogenous ordered-probit specification in Section 3.3, based on alternative definitions and treatments of the inheritance instrument. In all cases, the coefficient on stock-holding remains positive and statistically significant, and the magnitudes are close to those in the baseline specification.

Instrument Prevalence by Asset Group

Table A7: Prevalence of Inheritance Instrument by Investable Asset Group

Investable asset group	**Observations**	**Number with $Z_i = 1$**	**Share with $Z_i = 1$ (%)**
Low (< £5,000)	17,966	201	1.12
Medium (£5,000–£50,000)	11,113	273	2.46
High (≥ £50,000)	8,823	308	3.49
Missing	9,225	97	1.05

Notes: Table reports the distribution of the inheritance instrument Z_i by investable asset group for respondents with non-missing gender ($D1 \leq 2$). "Number with $Z_i = 1$" gives the count of individuals who report an inheritance in the last 12 months that is not associated with the death of a parent or spouse or with a serious accident of a close family member. "Share with $Z_i = 1$" is the corresponding percentage within each asset group.

Including Ambiguous Inheritances in the Control Group

First, we include respondents who both receive an inheritance and report the death or serious accident of a close family member, but set their instrument value to zero rather than excluding them from the sample. This treats these cases as non-instrumental inheritances. The resulting estimates are reported in Table A8.

Table A8: Endogenous Ordered Probit – Including Ambiguous Inheritances as Non-Instrumental

	Dependent Variable: Financial Literacy Score (Ordered)				
	(1)	(2)	(3)	(4)	(5)
Owns Stocks	1.500***	1.365***	1.309***	0.834**	0.862***
	(0.089)	(0.117)	(0.114)	(0.394)	(0.277)
Female	-0.351***	-0.402***	-0.392***	-0.515***	-0.472***
	(0.027)	(0.033)	(0.031)	(0.061)	(0.042)
Has Degree		0.358***	0.342***	0.509***	0.460***
		(0.031)	(0.026)	(0.064)	(0.039)
Income controls			Yes		Yes
Age controls				Yes	Yes
ρ	-0.530	-0.463	-0.454	-0.178	-0.228
$\Pr(\rho = 0)$	0.000	0.000	0.000	0.457	0.181
N	28,291	27,262	23,057	27,262	23,057

Robust standard errors in parentheses.

Estimation using Stata's `eoprobit` command with `vce(robust)` standard errors.

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

Instrument Excluding Only Deaths

Second, we define the instrument as an inheritance not associated with the death of a parent or spouse, but we do not exclude cases where respondents report a serious accident of a close family member. Observations with both inheritance and bereavement are dropped, as in the baseline specification. The corresponding estimates are shown in Table A9.

Any Inheritance as Instrument

Finally, we use a broad instrument that equals one for any reported inheritance receipt in the last 12 months, irrespective of the source or associated events. Table A10 reports the estimates for this specification.

Table A9: Endogenous Ordered Probit – Inheritance Instrument Excluding Parental and Spousal Deaths

	Dependent Variable: Financial Literacy Score (Ordered)				
	(1)	(2)	(3)	(4)	(5)
Owns Stocks	1.509***	1.373***	1.316***	0.881***	0.892***
	(0.086)	(0.113)	(0.111)	(0.330)	(0.254)
Female	-0.347***	-0.400***	-0.391***	-0.507***	-0.468***
	(0.027)	(0.032)	(0.030)	(0.054)	(0.040)
Has Degree		0.356***	0.341***	0.500***	0.456***
		(0.030)	(0.026)	(0.057)	(0.037)
Income controls			Yes		Yes
Age controls				Yes	Yes
ρ	-0.538	-0.470	-0.460	-0.208	-0.248
$\Pr(\rho = 0)$	0.000	0.000	0.000	0.304	0.114
N	27,957	26,931	22,771	26,931	22,771

Robust standard errors in parentheses.

Estimation using Stata's `eoprobit` command with `vce(robust)` standard errors.

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

Table A10: Endogenous Ordered Probit – Any Inheritance as Instrument

	Dependent Variable: Financial Literacy Score (Ordered)				
	(1)	(2)	(3)	(4)	(5)
Owns Stocks	1.572***	1.451***	1.393***	1.043***	1.020***
	(0.066)	(0.083)	(0.085)	(0.179)	(0.169)
Female	-0.331***	-0.382***	-0.376***	-0.481***	-0.450***
	(0.024)	(0.028)	(0.028)	(0.037)	(0.033)
Has Degree		0.338***	0.328***	0.472***	0.439***
		(0.026)	(0.024)	(0.038)	(0.031)
Income controls			Yes		Yes
Age controls				Yes	Yes
ρ	-0.585	-0.525	-0.512	-0.308	-0.327
$\Pr(\rho = 0)$	0.000	0.000	0.000	0.006	0.002
N	28,291	27,262	23,057	27,262	23,057

Robust standard errors in parentheses.

Estimation using Stata's `eoprobit` command with `vce(robust)` standard errors.

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

B Computational Appendix

B.1 Solving the Model

Given the model in Section 4.1, the Lagrangian is

$$\begin{aligned} V(s_t, m_t, \lambda_t, z_t, R_t^s) = \max_{c_t, s_{t+1}, m_{t+1}} \; & u(c_t) - \kappa(s_{t+1}, s_t, \lambda_t) + \beta \mathbb{E}[V_{t+1}(s_{t+1}, m_{t+1}, \lambda_{t+1}, z_{t+1}, R_{t+1}^s)] \\ & -\mu_t^A(c_t + s_{t+1} + m_{t+1} - z_t w_t - R_t^s s_t - R^m m_t) + \mu_t^B s_{t+1} \\ & +\mu_t^C(m_{t+1} - \underline{m}). \end{aligned} \tag{23}$$

Note that μ_t^A, μ_t^B, and μ_t^C are the Lagrange multipliers on the budget constraint, short-selling constraint, and borrowing constraint, respectively. From this, the first-order conditions with respect to c_t, s_{t+1}, and m_{t+1} are:

$$[c]: \quad u'(c_t) - \mu_t^A = 0, \tag{24}$$

$$[s_{t+1}]: \quad -\frac{\partial \kappa(s_{t+1}, s_t, \lambda_t)}{\partial s_{t+1}} + \beta \mathbb{E}\Big[\partial_{s_{t+1}} V_{t+1}\Big] - \mu_t^A + \mu_t^B = 0, \tag{25}$$

$$[m_{t+1}]: \quad \beta \mathbb{E}\Big[\partial_{m_{t+1}} V_{t+1}\Big] - \mu_t^A + \mu_t^C = 0. \tag{26}$$

The envelope conditions are

$$\partial_m V = \mu_t^A R_m \qquad = R_m u'(c_t), \tag{27}$$

$$\partial_s V = -\frac{\partial \kappa(s_{t+1}, s_t, \lambda)}{\partial s} + \mu_t^A R_s. \tag{28}$$

Thus, iterating Equation 27 forward by one period and substituting into Equation 24, we obtain the standard Euler equation.

$$\begin{aligned} u'(c) = \mu_t^A &= \beta \mathbb{E}\Big[\partial_{m_{t+1}} V'\Big] + \mu_t^C. \\ &= \beta \mathbb{E}\Big[R_m \mu_{t+1}^A\Big] + \mu_t^C. \\ &= \beta R_m \mathbb{E}\Big[u'(c_{t+1})\Big] + \mu_t^C. \\ u'(c_t) &\geq \beta R_m \mathbb{E}\Big[u'(c_{t+1})\Big] \end{aligned} \tag{29}$$

This inequality becomes strict if the borrowing constraints binds.

To solve this, we first assume that the FOC holds with equality, and invert the marginal utility to get optimal consumption given the m_{t+1} and s_{t+1} grid values that create $\partial_{m_{t+1}} V'$, and consequently, the policy of c_{t+1} given m_{t+1} and s_{t+1}. Thus,

$$c_{endo} = (u')^{-1}(\beta R_m \mathbb{E}[u'(c_{t+1})]), \tag{30}$$

where c_T comes from consuming all resources in the last period and any c_{t+1} for $t < T-1$ comes from the solved consumption policy in the following period. Given that we impose CRRA utility, we have

$$c_{endo} = (\beta R_m \mathbb{E}[(c_{t+1})^{-\sigma}])^{-\frac{1}{\sigma}}. \tag{31}$$

We will solve the utility for all fixed options of s_{t+1} and assume that the stock level today, s, lies on the grid. Let us denote a variable, X, on our exogenous grid by X^{grid}. We solve the the cash holding in the current period, m_{endo} that justifies saving s_{t+1}^{grid} and m_{t+1}^{grid} and consuming c_{endo} given that agents have s^{grid} today. Thus, using the budget constraint,

$$m_{endo} = \frac{c_{endo} + s_{t+1}^{grid} + m_{t+1}^{grid} - zw - R_t^s s^{grid}}{R_m}. \tag{32}$$

We will now interpolate the consumption policies back to the exogenous grid, rather than our m_{endo} endogenous grid. We will do this taking the s_{t+1} choice as fixed, solving for each value of s_{t+1}^{grid}. Rather than choosing the value of stocks that directly maximizes the utility, we will take the "soft-max" or logit probabilities over the intermediate value functions, $\tilde{V}_t$, to compute the probability with which each action is chosen, maintainig that actions associated with higher value are chosen with a higher probability. These intermediate value functions are defined as

$$\begin{aligned} &\tilde{V}_t(s_t, m_t, \lambda_t, z_t, R_t^s; \hat{s}_{t+1}) := \\ &\quad \max_{c_t, m_{t+1}} u(c_t) - \kappa(s_t, \lambda_t, \hat{s}_{t+1}) + \beta \mathbb{E}\left[V_{t+1}(\hat{s}_{t+1}, m_{t+1}, \hat{\lambda}_{t+1}, z_{t+1}, R_{t+1}^s)\right], \end{aligned} \tag{33}$$

where $\hat{\lambda}_{t+1}$ denotes the evolution of financial literacy conditional on the choice of $\hat{s}_{t+1}$. The probability of each choice of s_{t+1} is determined by a standard logit form derived from the Gumbel-distributed taste shocks,

$$\Pr(\hat{s}_{t+1} \mid \tilde{V}_t) = \frac{\exp\left(\frac{1}{\xi}\tilde{V}_t(s_t, m_t, \lambda_t, z_t, R_t^s; \hat{s}_{t+1})\right)}{\sum_{s_{t+1}} \exp\left(\frac{1}{\xi}\tilde{V}_t(s_t, m_t, \lambda_t, z_t, R_t^s; s_{t+1})\right)}, \tag{34}$$

where ξ governs the degree of taste dispersion (or choice "temperature") in the soft-max operator. The final value function is then given by the log-sum formula:

$$V_t(s_t, m_t, \lambda_t, z_t, R_t^s) = \xi \log\left(\sum_{s_{t+1}} \exp\left[\frac{1}{\xi}\tilde{V}_t(s_t, m_t, \lambda_t, z_t, R_t^s; s_{t+1})\right]\right). \tag{35}$$

B.2 Calibration – Additional Results

Table B1 reports the calibrated stock returns and associated probabilities.

Table B1: Discretized Two-Year Gross Returns on Global Equity

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Net Return (%)	-27.3	-16.6	-5.9	4.8	15.5	26.2	36.9	47.6	58.3	69.0
Probability	2.5	5.4	9.8	14.6	17.7	17.7	14.6	9.8	5.4	2.5

Notes: Table reports a ten-point discrete approximation of two-year gross returns for the FTSE All-World Total Return Index. The empirical return distribution is modelled as normal with a mean net return of 20.9% and a standard deviation of 24.1%. Probabilities reflect normalized density weights evaluated at each grid point. Returns are shown in percent and include reinvested dividends.

Table B2 shows the cut-points of the financial literacy scores that correspond to the continuous financial literacy levels in the model. These are computed given the calibration of λ^0 and Λ in Table 6.

Table B2: Initial Financial Literacy Categories and Latent Ability Cut-points

Score FL_i	Lower cutpoint	Upper cutpoint	Share among ages 18–24 (%)
0	$-\infty$	3.32	1.4
1	3.32	5.48	14.4
2	5.48	9.06	24.7
3	9.06	14.98	26.4
4	14.98	$+\infty$	33.1

Notes: Cutpoints are expressed in units of the latent financial literacy index λ. Shares correspond to the empirical distribution of financial literacy scores among households aged 18–24 in the Wealth and Assets Survey (WAS).

B.3 Policy Analysis – Additional Results

Table B3: Final Working-Age Moments: Literacy Programs

	Participation	Stocks	Total Wealth	Avg. Fin. Lit.	Consumption
Baseline	51.3%	0.36	1.60	13.21	1.35
Age 20	63.3%	0.48	1.63	15.86	1.37
	(24.0%)	(34.6%)	(1.9%)	(20.0%)	(2.0%)
Age 26	63.1%	0.48	1.63	15.79	1.37
	(23.5%)	(33.5%)	(1.8%)	(19.5%)	(1.9%)
Age 32	62.8%	0.47	1.63	15.73	1.37
	(22.9%)	(32.3%)	(1.8%)	(19.1%)	(1.9%)
Age 40	62.2%	0.47	1.63	15.71	1.37
	(21.8%)	(31.0%)	(1.9%)	(18.8%)	(1.9%)

Notes: Participation is shown in percent, rounded to one decimal place. Moments are evaluated at period $T-R$ (age 64). Percentage deviations are relative to the baseline.

Table B4: Final Working-Age Moments: Cash vs. Stock Transfers

	Participation	Stocks	Total Wealth	Avg. Fin. Lit.	Consumption
Baseline	51.3%	0.36	1.60	13.21	1.35
Age 20					
Cash transfer	51.3%	0.36	1.60	13.24	1.35
	(0.1%)	(0.3%)	(0.0%)	(0.2%)	(0.0%)
Stock transfer	82.3%	0.63	1.67	18.73	1.41
	(61.8%)	(76.6%)	(4.7%)	(41.7%)	(4.7%)
Age 26					
Cash transfer	51.3%	0.36	1.60	13.24	1.35
	(0.1%)	(0.3%)	(0.0%)	(0.2%)	(0.0%)
Stock transfer	81.4%	0.62	1.67	18.42	1.41
	(60.0%)	(72.9%)	(4.6%)	(39.4%)	(4.5%)
Age 32					
Cash transfer	51.3%	0.36	1.60	13.24	1.35
	(0.1%)	(0.3%)	(0.1%)	(0.2%)	(0.0%)
Stock transfer	82.0%	0.62	1.67	18.35	1.41
	(61.1%)	(72.5%)	(4.6%)	(38.9%)	(4.5%)
Age 40					
Cash transfer	51.3%	0.36	1.60	13.24	1.35
	(0.1%)	(0.5%)	(0.3%)	(0.2%)	(0.1%)
Stock transfer	83.8%	0.61	1.66	18.32	1.40
	(64.8%)	(70.9%)	(4.0%)	(38.6%)	(4.2%)

Notes: Participation is shown in percent, rounded to one decimal place. Moments are evaluated at period $T-R$ (age 64). Percentage deviations are relative to the baseline.