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Optimal Financial Knowledge and Wealth Inequality in an Overlapping Generations Setting

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Abstract: Despite rising wealth inequality and persistently low levels of financial literacy in the United States, little is known about how financial knowledge and intergenerational dynamics interact to shape wealth outcomes. While existing studies on wealth inequality have explored the impacts of financial literacy and intergenerational links in isolation, this study examines the interaction between these factors. We apply a framework of endogenous financial knowledge accumulation to an overlapping generations model in which generations are connected by the inheritance of wealth, educational attainment probabilities, and financial knowledge. We calibrate the model to U.S. data and find that heterogeneity in financial knowledge modestly increases inequality, raising the Gini coefficient on wealth by 0.02 points. While the inherited component of financial knowledge has little effect on inequality in our setting, we find evidence that early-life financial knowledge significantly influences lifetime wealth, suggesting its potential to drive inequality in settings with greater heterogeneity.

Keywords: Wealth Inequality, Financial Literacy, Heterogeneous Returns, Intergenerational Links, Overlapping Generations Model

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"Fixing errors typically improves results." –Anonymous

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1 Introduction

While wealth and wealth inequality are difficult to measure, evidence suggests that since the late 1970s, wealth inequality in the United States has risen sharply (Saez and Zucman, 2016). The World Inequality Database (2025) estimates that the share of wealth held by the wealthiest one percent of Americans rose from 23.2% to 34.8% between 1980 and 2023. The median net wealth of the richest five percent of households grew by over 88% between 1998 and 2007 alone (Horowitz et al., 2020). Further, average household wealth varies widely by race and education: for example, Black households hold significantly less wealth than White households on average ($\$311,000$ compared to $1.4 million), and households headed by someone with less than a high school diploma hold 9 cents for every dollar of wealth held by households whose head earned a four-year college degree (Kent, 2025).

At the same time, many Americans lack basic financial literacy skills. In 2024, U.S. adults on average answered only two out of five simple financial literacy questions correctly, with large gaps in average scores by gender, race, and generation (Yakoboski et al., 2024). The 2022 National Financial Capability Study[1] showed that scores on their financial literacy test declined during the period from 2009 to 2021, particularly among younger adults, women, and Black respondents (Urban and Valdes, 2022).

Understanding the causes of wealth inequality is crucial for developing efficient and functional policy to address it, but these causes are not yet fully understood. While it is clear that there is a relationship between financial literacy and wealth at an individual level (e.g., a person who is highly financially literate is expected to grow their wealth faster than someone who is not), it is not obvious what financial literacy's role is in causing wealth inequality at a societal level. However, it is often the case that groups holding the least wealth are also the least financially knowledgeable, indicating that this relationship warrants further study.

Our model applies the endogenous financial literacy acquisition process outlined by Lusardi et al. (2017) to an overlapping generations (OLG) model calibrated to match U.S. data, which includes bequests as well as uncertainty in income and capital market returns. This allows us to capture how more financially literate agents can more profitably allocate their resources to achieve a higher rate of return on their savings. We further allow for intergenerational links through the inheritance of financial knowledge and educational attainment. Our study evaluates the dynamics of the aforementioned

[1] FINRA Investor Education Foundation's National Financial Capability Study

model against an alternative specification without intergenerational transmission of financial knowledge, a specification with a uniform distribution of financial knowledge, and a specification without a bequest motive.

Using this framework, we seek to answer two important questions: (1) Does including endogenous financial literacy acquisition in a model help generate wealth inequality in an overlapping generations setting? (2) How can intergenerational transmissions of financial knowledge enrich that model?

We find that our model captures key life cycle patterns in income, wealth, financial knowledge, and portfolio allocation. It further replicates the intergenerational correlation in risky asset holdings. While our calibrations fall short of generating the wealth inequality observed in U.S. data, the findings highlight the roles of financial knowledge and its intergenerational transmission in modeling and shaping wealth dynamics. Counterfactual analyses show that both bequest motives and endogenous financial knowledge accumulation contribute to wealth inequality, although the effects are modest due to limited heterogeneity.

The remainder of the paper is structured as follows: Section 2 provides an overview of the relevant existing literature. Sections 3 and 4 introduce the model and its calibration. Section 5 presents and discusses the results of the study. Finally, we summarize the key findings in Section 6.

2 Literature Review

In incorporating financial literacy into an overlapping generations model to generate inequality, our study draws on concepts from two bodies of existing literature on wealth inequality and financial knowledge.

2.1 Wealth Inequality

Early economic models relied on heterogeneity in income and on households self-insuring against negative earnings shocks by means of personal savings (i.e., precautionary savings) to explain wealth inequality. While these models are able to capture sizable parts of the wealth distribution, models based on precautionary savings against idiosyncratic earnings shocks do not fully account for the wealth distribution seen in the data (Quadrini and Ríos-Rull, 1997). Therefore, researchers lean on other observable factors to explain the cross-sectional differences in wealth holdings.

One influential strand of the literature focuses on incorporating family relationships (i.e., intergenerational links) into the models. De Nardi (2004) develops a general equilibrium OLG model in which parents and children are connected by accidental and voluntary bequests as well as by inheritance of earnings ability. This framework accounts for more of the observed wealth inequality while maintaining realistic savings behavior over the life cycle. Building on this, De Nardi et al. (2009) add medical expenses to the model, concluding that medical expense risk is a key driver for wealth accumulation for the elderly—more so than the desire to leave a bequest.

A further important approach emphasizes heterogeneity in earnings and returns. Cagetti and De Nardi (2006) and Benhabib et al. (2011) adjust OLG models to better match the upper tail of the wealth distribution. The former does so by introducing occupational choice and entrepreneurship to a model with bequests, where the entrepreneur's wealth acts as collateral for debt. Using that approach, they generate a wealth distribution similar to the one found in data. The latter focuses on capital income risk: Benhabib et al. (2011) find that capital income risk and idiosyncratic returns to wealth are crucial for generating the long tails of the wealth distribution.

Another key factor explored in the existing literature is life cycle uncertainty. Storesletten et al. (2004) study how consumption inequality evolves with age. They find that idiosyncratic earnings risk with near unit root persistence, the equilibrium amount of aggregate wealth in the economy, and the presence of a U.S.-type social security system are key determinants to model consumption inequality. Further, they conclude that 47% of an agent's lifetime uncertainty is resolved prior to entering the labor market, with the remainder stemming from differences after labor market entry, significantly differing from Keane and Wolpin (1997) who estimate the proportion to be 90% using other methods. Huggett et al. (2011) build upon this idea by examining the role of educational investment and human capital formation on lifetime earnings, wealth, and utility. They show that early-life differences in initial wealth, human capital, and learning ability explain more of the variation in lifetime outcomes than shocks experienced later in life. Among these factors, variation in human capital is identified as the most important. Therefore, while the estimates vary across studies, both initial conditions and shocks experienced throughout the lifetime are important in modeling inequality.

2.2 Financial Literacy

Evidence suggests that financial literacy plays an important role in savings behavior. There are strong correlations between financial literacy score and contributions to retire-

ment savings (Yakoboski et al., 2024). Less financially literate consumers spend more on transaction fees, face higher interest rates on loans, and assume more debt (Lusardi and Tufano, 2015; Lusardi and de Bassa Scheresberg, 2013) while also accumulating lower levels of savings (Stango and Zinman, 2009; Klapper et al., 2015). Further, Lusardi and Mitchell (2011) and Lusardi et al. (2015) suggest through theoretical models that financial literacy interventions could increase retirement savings among agents. These findings indicate that financial literacy could help to bridge the gap between models and the real world wealth distribution.

Clark et al. (2017) provide further evidence for the importance of financial knowledge by linking administrative data on 401(k) investment performance with individual financial literacy levels. Their results show that the most financially sophisticated participants allocated a larger share to stocks and achieved a higher rate of return while holding portfolios with less idiosyncratic risk compared to the least sophisticated group. Notably, however, the authors also find the portfolios of sophisticated investors to be significantly more volatile. Examining portfolio choice after the intervention (i.e., after participating in the survey) showed that respondents displayed improved equity allocation and higher expected returns.

Lusardi et al. (2017) test how financial literacy affects savings and inequality. The authors construct a stochastic life cycle model with endogenous accumulation of financial knowledge with uncertainty and imperfect insurance, taking into account education levels. In their model, accumulation of financial knowledge allows agents to better allocate lifetime resources and earn a higher return on their savings. The model generates significant wealth inequality relative to a simpler specification (i.e., a one asset saving model), and the authors estimate that 30–40% of retirement wealth inequality can be attributed to financial knowledge.

2.3 Contributions to Literature

We further the investigation of how financial knowledge can help model inequality by applying Lusardi et al. (2017)'s model to an overlapping generations model. Specifically, we aim to understand how modeling financial knowledge accumulation interacts with bequest motives and other intergenerational links. To this end, we base our OLG setting on De Nardi (2004)'s model in which generations are linked by luxury bequests and inherited labor productivity.

Additionally, we enrich the links between generations by allowing a proportion of financial literacy to be passed down from parents to children. In doing so, we further contribute to existing research on dynasties. While Benhabib et al. (2022) demonstrate that persistent heterogeneity in the rate of return to wealth across generations is important in explaining the wealth distribution, they do not explicitly model the mechanisms behind such persistence. The financial knowledge inheritance in our model provides one possible mechanism for understanding this persistent heterogeneity.

3 Model

3.1 Demographics

Agents enter the model at age 22 ($t = 1$), at which point they contribute fully to the economy by working, saving, consuming, and investing. Agents are born with a fixed education level α (either less than high school education, a high school diploma, or university education). At age 25 ($t = 4$), each agent exogenously has one child.

Agents work and earn uncertain labor income until retirement at age 65 ($t = 44$) at which point they receive a fixed pension from the government. They also live for certain until retirement, a minor simplification that allows us to ensure that all children outlive their parents, simplifying the modeling of bequests. Beginning at retirement, agents face a positive and increasing probability of death in each period and die in period T, for certain by by age 90 ($t = 69$).

Like De Nardi (2004), we do not model any inter vivos transfers of wealth, so agents begin their working lives with zero assets. Generations are, however, linked by bequests, inheritance of education probabilities, and inheritance of financial knowledge. An overview of the timing of this model is presented in Figure 1.

3.2 Preferences

Agents are assumed to have constant relative risk preferences, so utility is given by

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

where c_t is an agent's consumption in period t and the risk aversion parameter γ is strictly greater than one.

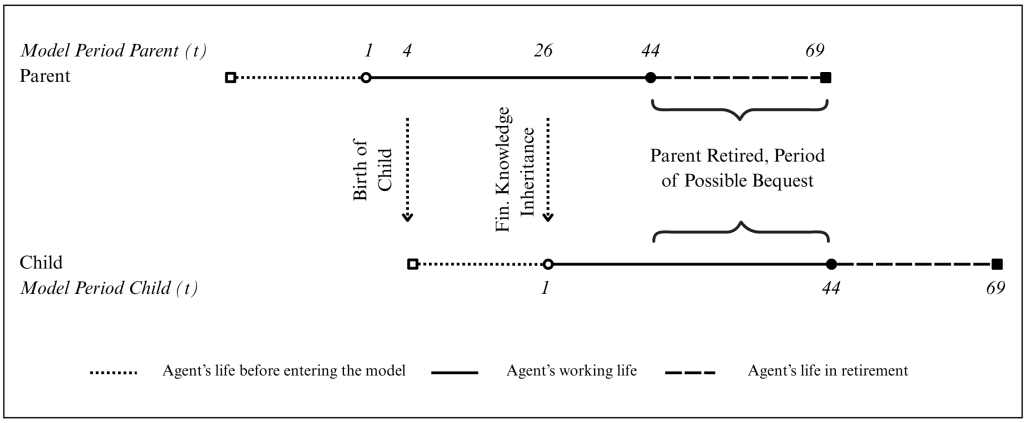


Figure 1: Main model dynamics illustrated for two generations.

Agents also derive utility from leaving a bequest to their children at death. As in De Nardi (2004), we model bequests as a luxury good, though for interpretability purposes we use the functional form of the threshold bequest motive in Lockwood (2012)

$$v(b) = \theta_1 \frac{(\theta_2 + b)^{1-\gamma}}{1-\gamma}, \tag{2}$$

where b is the sum left to the child net of estate taxes, θ_2 determines the wealth threshold below which an agent will not leave a bequest, and θ_1 determines the strength of the bequest motive.

3.3 Government

The government levies taxes on labor income, capital income, and bequests (τ_l, τ_c, and τ_b, respectively). These taxes are used to fund pensions, although we do not require that the government balances its budget.[2]

[2]In our main model, we find that the government runs a surplus of $\$3,000$ per person per year. We refrain from calibrating the taxes and transfers to balance the budget due to computational constraints.

3.4 Financial Markets

Following the approach outlined in Lusardi et al. (2017), agents are given the choice to invest their savings in a risk-free asset (e.g., government bonds, or keeping wealth in a savings account) and a risky asset (e.g., stocks).[3] The former yields a low, risk-free rate of return $\bar{r}$, which is independent of the agent's financial knowledge, while the latter yields a higher, risky rate of return above the risk-free rate. The rate of return of the risky asset is stochastic, with an expected return that depends on f_t, the agent's level financial knowledge in period t. The stochastic return function is given by

$$\tilde{r}(f_t) = \bar{r} + r(f_t) + \sigma_\lambda \lambda_t \,, \tag{3}$$

where $\sigma_\lambda \lambda_t$ is a stochastic shock, σ_λ is a scalar, and $\lambda_t \sim \mathcal{N}(0,1)$.[4] Assuming that return shocks among individuals are uncorrelated is a strong assumption. However, research shows that savings portfolios exhibit a high level of idiosyncratic risk, thus providing support for this simplification.[5]

The function $r(f_t)$ represents the excess return function and is linearly increasing in f_t. As financial knowledge is bounded by $f_t \in [0, 100]\ \forall t$, we set the excess return such that $r(0) = r_{min} = 0$ and $r(100) = r_{max}$. As the variance of the stochastic return function is fixed, agents with more financial knowledge also obtain a better-risk adjusted return (i.e., a higher Sharpe Ratio).

An agent's overall portfolio return is the weighted return between the basic and risky asset holdings

$$\tilde{r}_\kappa(f_t) = (1 - \kappa_t)\, \bar{r} + \kappa_t\, \tilde{r}(f_t) \,, \tag{4}$$

where κ_t denotes the share of savings allocated to the risky asset in period t. Investment in the risky asset comes at a per-period lump sum cost c_d (i.e., an annual stock market participation cost).

[3] Henceforth, we use the terms risky assets and stocks interchangeably.

[4] This follows the stochastic return function in Kim (2024) and is a slight deviation from Lusardi et al. (2017), whose returns are log-normally distributed.

[5] See for example Tang et al. (2010), who find that while most 401(k) plan sponsors offer efficient portfolios, many participants construct inefficient portfolios due to poor diversification and over-concentration in certain assets (e.g., company stock), leading to high idiosyncratic risk and reduced retirement wealth by up to 20%.

3.4.1 Financial Knowledge

Lusardi et al. (2017) posit that all agents enter the model without financial knowledge, which they can accumulate through monetary investments in their financial literacy until the age of retirement. Further, each period, an agent's stock of financial knowledge depreciates at the rate δ_f. Diverging from Lusardi et al. (2017)'s approach, we allow some agents to enter the model with a higher level of financial literacy through inherited knowledge. To capture the channel of knowledge transfer, we model that each agent, upon entering the model, is endowed with a share ψ of their parent's financial knowledge in the same year.[6] Therefore, we modify the accumulation process of financial knowledge to

$$f_{child,\, t=1} = \psi \cdot f_{parent,\, t=26} \quad \text{and} \quad f_{t+1} = \begin{cases} (1-\delta_f)\, f_t + i_t, & t = 1, 2, \ldots, 43 \\ (1-\delta_f)\, f_t, & t = 44, 45, \ldots, T-1 \end{cases}, \tag{5}$$

where investments in financial knowledge are constrained such that $f_t \in [0, 100]\ \forall t$. In each period of their working lives, agents choose i_t, which represents how much they increase their financial knowledge (and by extension, how much they wish to increase their expected return to the risky asset above the risk free rate of return $\bar{r}$). Increasing f_{t+1} by i_t points comes at a cost of $\pi(i_t)$. The function $\pi(i_t)$ is assumed to be strictly convex, reflecting decreasing returns to investment in financial knowledge:

$$\pi(i_t) = \pi_0 \, (i_t)^{\pi_1}, \tag{6}$$

where π_0 is the base cost of financial knowledge and π_1 is the exponent governing the curvature of the cost function.

Lusardi et al. (2017) note that little is known about heterogeneity in the cost of acquiring financial knowledge and therefore refrain from assuming different cost function depending on agent's education level or other demographic heterogeneity. In our model, we follow the same approach: we remain agnostic about the potential differences in cost functions and assume that all agents face the same cost of acquiring financial knowledge.

[6] When a child enters the model at age 22 ($t = 1$), their parent is 47 ($t = 26$). Thus, in the first period, agents receive a share of their parent's f_{26}. Note that agents in the first generation, in absence of inherited knowledge (ψ), enter the model with no previous financial knowledge (i.e., $f_1 = 0$).

3.5 The Agent's Problem

Agents maximize their lifetime value by choosing savings a_t, the share of savings allocated to risky assets κ_t, and their investment in financial knowledge i_t. Borrowing is constrained such that $a_t \geq 0 \; \forall t$.

A working agent's state is given by $y_t = (\alpha,\ t,\ x_t,\ f_t,\ z_t)$ where α refers to the agent's education level, t is the agent's age, x_t is cash on hand in period t, f_t is the agent's financial knowledge in period t, and z_t is the agent's current persistent income shock. Retired agents lack a z_t state as their income is fixed.

3.5.1 Working Agents

From $t = 1$ to $t = 43$ (corresponding to ages 22 to 64) agents earn uncertain income from labor and survive for certain until the next period. These agents have the value function

$$
\begin{aligned}
W(\alpha, t, x_t, f_t, z_t) = \max_{a_t \geq 0,\ \kappa_t,\ i_t} \Bigg\{ & \frac{\left(x_t - a_t - \pi(i_t) - c_d \mathbb{1}(\kappa_t > 0)\right)^{1-\gamma}}{1-\gamma} \\
& + \beta E_t W(\alpha, t+1, x_{t+1}, f_{t+1}, z_{t+1}) \Bigg\} \\
\text{subject to:} \quad x_{t+1} &= \left(1 + \tilde{r}_\kappa(f_{t+1})(1-\tau_c)\right) a_t + y_{t+1}(1-\tau_l) \\
y_{t+1} &= \exp\left(k_\alpha(t+1) + z_{t+1} + \epsilon_{t+1}\right) \\
f_1 &= \psi \cdot f_{\text{parent},\, t=26} \\
f_{t+1} &= (1-\delta_f) f_t + i_t \,,
\end{aligned}
\tag{7}
$$

where $W(\alpha,\ 44,\ x_{44},\ f_{44})$ is equivalent to $V(\alpha,\ 44,\ x_{44},\ f_{44},\ z_{44})$ as described in Section 3.5.2. Agents receive one bequest during their working age, in the period in which their parent dies. For simplification, agents do not expect this windfall and thus do not adjust their behavior in anticipation.

Income is modeled using an education-dependent age polynomial, a persistent income shock, and an idiosyncratic income shock. Thus log income at age t for an agent with education level α is given by:

$$
\log\ y_{\alpha,t} = k_\alpha(t) + z_t + \epsilon_t \,, \tag{8}
$$

where $k_\alpha(t)$ is a fourth-order age polynomial which we allow to vary for the three different education groups, z_t is a persistent shock to income, and ϵ_t is the stochastic component of the income shock which satisfies $\epsilon_t \sim \mathcal{N}(0,\ \sigma_\epsilon^2)$.

The persistent shock to income z_t is modeled as a first-order autoregressive process as shown in Equation 9, which implies a first-order Markov chain. That is, conditional on z_{t-1}, the distribution of z_t is independent of past values $z_{t-2},\ z_{t-3}, \ldots$

$$z_t = \rho\, z_{t-1} + \eta_t \text{ with } \eta_t \sim \mathcal{N}(0,\ \sigma_\eta^2) \tag{9}$$

Provided the process is stationary (i.e., $|\rho| < 1$ is fulfilled) and the shock term η_t is normally distributed, the underlying continuous AR(1) process will have a stationary distribution that is normal in the long run. The Rouwenhorst discretization[7] approximates this process with a finite-state Markov chain (as we can only have a finite number of z_t states) whose invariant distribution resembles a normal distribution, especially as the number of grid points increases (Kopecky and Suen, 2010).

3.5.2 Retired Agents

From age 65 ($t = 44$) and onward, agents are retired and receive a certain income of $B_\alpha \bar{Y}_\alpha$, where $\bar{Y}_\alpha$ is the mean income for a working agent in the same education group and B_α is an education group-specific income replacement rate. As in Lusardi et al. (2017), retired agents cannot acquire new financial knowledge, though they still choose their risky share of investment κ_t. Retired agents face a positive probability of death ξ_t in the next period (with $\xi_{69} = 1$ at age 90) and derive utility from leaving a bequest for their child as described above. Bequeathed savings are realized at the risk-free rate $\bar{r}$ in the period of inheritance to simplify calculations.

[7] This process can only be used to discretize highly persistent processes (i.e. those with a high value for ρ). Our ρ satisfies this condition as it is 0.95 throughout.

Thus, retired agents maximize

$$V(\alpha, t, x_t, f_t) = \max_{a_t \geq 0,\, \kappa_t} \left\{ \frac{(x_t - a_t - c_d \mathbb{1}(\kappa_t > 0))^{1-\gamma}}{1-\gamma} + (1-\xi_t)\beta E_t V(\alpha, t+1, x_{t+1}, f_{t+1}) + \xi_t \theta_1 \frac{(\theta_2 + a_t(1+\bar{r}(1-\tau_c))(1-\tau_b))^{1-\gamma}}{1-\gamma} \right\} \tag{10}$$

$$\text{subject to:} \quad x_{t+1} = (1 + \tilde{r}_\kappa(f_{t+1})(1-\tau_c))\, a_t + B_\alpha \bar{Y}_\alpha (1-\tau_l)$$
$$f_{t+1} = (1-\delta_f) f_t \,.$$

By the time agents reach retirement, their parent has died for certain. Thus, agents cannot receive bequests in retirement.

3.6 Solving the Model

We begin by determining optimal choices for agents in the last period using first order conditions, discretizing our continuous variables, and modeling the z_t process using the Rouwenhorst method.

Then, we solve our model using backwards induction: at each possible state, we apply the derivative-free, simplex-based Nelder-Mead method to find an agent's optimal savings behavior, investment in financial literacy, and investment in risky assets using information about their value function in the next period. In addition to the zero borrowing limit, agents are restricted from saving more than 99.9% of their cash on hand for computational ease, though this constraint is nonbinding for all agents. The optimization process also separately considers and compares optimal choices with and without investment in risky assets to account for the discontinuity in the objective function caused by the lump-sum cost of investing in risky assets c_d.

Optimization is performed on a grid of 100 unevenly spaced points for cash on hand and an evenly spaced grid of 100 points for financial knowledge. Moreover, in discretizing the shocks z, ϵ, λ, we use grids of $N_z = 5$, $N_\epsilon = 5$, and $N_\lambda = 7$ points. Optimal choices and values for off-grid levels of cash on hand or financial knowledge are acquired via bilinear interpolation on the two-dimensional grid. We apply flat extrapolation above the grid to prevent agents from considering f values above the maximum of 100 while

ensuring that the maximum of the cash on hand grid is sufficiently high to ensure that agents cannot reach or consider higher cash on hand values.

After solving the dynamic optimization model and obtaining the optimal policy functions, we simulate the life-cycle behavior of agents across multiple generations. Each simulation spans 10 generations of $10,000$ agents, with 69 periods corresponding to ages 22 to 90.

First, we simulate exogenous processes for the entire population of agents. For each agent, we draw their educational state α from a discrete distribution based on parental education. The first generation ($m = 1$) of agents receive their education fixed effects based on the distribution found in the Panel Study of Income Dynamics (PSID).[8] Further, we simulate stochastic income components z and ϵ, return shocks λ, and each agent's age of death.

Next, for each generation and each period, we simulate each agent's choices of savings, investment in financial knowledge, and investment in risky assets when facing these shocks using the previously computed optimal policy functions. Here, when an agent enters the model in $t = 1$ (age 22), we endow them with the proportion ψ of their parent's financial knowledge in the same period. At death, the agent's last period savings net of taxes are transferred to their child in the following period.

The results of the simulation are considered after $m = 10$ generations to allow for convergence.

4 Calibration

Our model is calibrated using parameters from two sources: existing research and U.S. data. As we seek to replicate Lusardi et al. (2017)'s model in an OLG setting, we use their parameters whenever possible. For parameters that can be calibrated using real world, U.S. data, we rely heavily on the PSID, with the exception of mortality data, which is taken from the Centers for Disease Control and Prevention (CDC).[9] Table 3 provides an overview of the parameters used in the model.

[8] Panel Study of Income Dynamics, 2025. Hereinafter referred to as the PSID. See Appendix A for detailed information on data processing.
[9] National Center for Health Statistics, 2025

4.1 Calibration of Labor Income Process

To estimate the age-specific labor income variation, we construct a fourth-order age polynomial for each education group ($k_\alpha(t)$) using PSID data. Education groups are defined in Section 4.2. Household income is computed as the sum of the household's head and spouse's labor and transfer incomes. For married and cohabiting individuals, income is divided by two to approximate individual-level earnings. Separately for each education group, we estimated the following regression:

$$\log\, y_{it} = \delta_0 + \delta_1\, \text{age}_{it} + \delta_2\, \text{age}_{it}^2 + \delta_3\, \text{age}_{it}^3 + \delta_4\, \text{age}_{it}^4 + \epsilon_{it}\,, \tag{11}$$

where $\log\, y_{it}$ is the log of an individual's income at time t (in 2015 US dollars) and age_{it} is the individual's age. Figure 2 shows the age polynomials compared to the values in the PSID data. Income paths of the different education groups differ notably: the more educated groups earn a higher income throughout their life cycle, while also increasing their earnings at a higher rate.

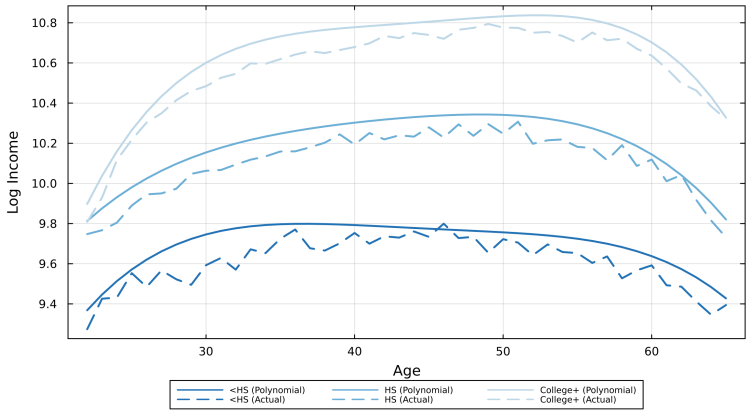


Figure 2: Actual and estimated labor income paths.

4.2 Calibration of Intergenerational Links in Educational Attainment

To determine intergenerational links in education probability (i.e., the probability of a certain educational outcome for a child given their parents' educational attainment), we use the PSID's Family Identification Mapping System (FIMS) to match parents and

children during the periods in which PSID wealth data is available, 1999–2021. During this period, the PSID surveyed its respondents biennially.

We first define a person's educational status as the number of years of education that they have completed by age 30. We then calculate the average years of education of all of a given child's parents that are present in the data. The average parental education and the child's years of education are categorized into less than high school (<HS: years of schooling ≤ 11), high school (HS: years of schooling $= 12$), and college or more (C+: years of schooling ≥ 13).

Then, we compute the conditional probabilities of a child achieving a certain education level (<HS, HS, C+), given their parent's education level. Table 1 shows the result with the parent's education level in column one and the probabilities of their child's educational outcome in the remaining columns.

Table 1: Children's education attainment probabilities by parental education.

Parent \ Child	**<HS**	**HS**	**C+**
<HS	0.244	0.457	0.299
HS	0.084	0.425	0.491
C+	0.029	0.207	0.764

<HS: Less than High School, **HS:** High School, **C+:** Some College or more

4.3 Calibration of Financial Components

Lusardi et al. (2017) set the annual participation cost for the stock market c_d to \$750, using an inflation adjusted median value from Vissing-Jorgensen (2003). The estimate takes into consideration the monetary and time costs of acquiring basic financial knowledge, cost and time spent setting up accounts, time spent filing taxes, brokerage fees, time spent implementing trades, bid-ask spreads, and costs associated with load mutual funds. Since then, however, technological advancement, shifts in investor preferences, and regulatory action have reduced the threshold to access financial markets.

Many banks now offer investment into a wide range of products through online banking, with little time effort needed to open brokerage accounts. Further, standalone brokerage services such as Robinhood and Fidelity, among others, further widen the range of

low-cost, low-time-investment services that allocate assets to global markets. While free offerings exist, full access to markets can be gained through paid services like Robinhood Gold with an annual cost of $50 (Robinhood Markets, 2025).

In addition to the simplified market access, Duvall (2021) finds that the share of gross sales of long-term mutual funds going to no-load funds increased significantly in the period from 2000 to 2020.[10] For the same time period, the mutual fund expense ratio has dropped significantly. Moreover, the U.S. Security and Exchange Commission recently took action to decrease access cost to reduce transaction cost for all investors (U.S. Securities and Exchange Commission, 2024).

Therefore, we posit that the stock market participation rate has decreased substantially since the publication for prior literature and allow for lower values of c_d in our calibration.

Additionally, while Lusardi et al. (2017) set $r_{max} = 0.04$ (such that the average stock market return for an agent with perfect financial knowledge was $\bar{r} + r_{max} = 0.06$, matching the equity premium commonly used in the portfolio literature), we posit that r_{max} should be set higher, allowing agents with very high financial knowledge to earn higher average returns than the market. Thus, we set $r_{max} = 0.06$ for our calibration.

4.4 Internal Calibration

We jointly calibrate the risk aversion parameter, the parameters of the bequest motive, the cost of financial knowledge, and the stock market participation cost (γ, θ_1, θ_2, π_0, and c_d) to match moments retrieved from data and related literature using iterative methods. In calibration, we target the average share of risky assets conditional on stock market participation $\mathbb{E}[\kappa \mid \kappa > 0] = 0.43$ found in Cupák et al. (2022). Further, we aim to calibrate our model to reflect realistic (i.e., hump-shaped) wealth, financial knowledge, and stock market participation profiles. Lastly, we target median wealth holdings at age 50 of approximately $\$200,000$, as estimated by Aladangady et al. (2023).

Calibrating the model using $\gamma = 5.0,\ \theta_1 = 9,000,\ \theta_2 = 100,000,\ \pi_0 = 500,\ \pi_1 = 1.75,$ and $c_d = 150$, we match median wealth at age 50 relatively well with $\$214,982$, overestimating the target by 7.5%. Calibrating the conditional stock market participation rate proved more difficult with $\mathbb{E}[\kappa \mid \kappa > 0] = 0.61$, an overestimation of 0.18 points above the target of 0.43.

[10] A no-load fund is a fund that charges no sales fees on either the front or back end of the transaction (Vanguard Group Inc, 2025). In 2000, 46% of gross sales went to no-load products; by 2020, the share had increased to 88% (Duvall, 2021).

4.5 Calibration of Inherited Financial Knowledge

An individual's financial knowledge level as modeled in our framework is not directly observable in the data. While financial literacy surveys exist, there is insufficient data on parent-child pairs to make directly estimating the intergenerational link feasible. Therefore, we proxy for this relationship by adjusting the inheritance of financial knowledge to match the correlation between the parent's and child's share of net worth allocated to risky assets.

To calibrate the inherited proportion of financial knowledge ψ, we take a two stage approach. First, we estimate the relationship between the risky share of parents' assets and those of their children in PSID data using Equation 12, where, as in our model, κ_{it} is the share of wealth invested in riskier financial assets, a_{it} is savings, and y_{it} is labor income. Γ is a vector of coefficients for the education dummy variables.

$$\kappa_{it} = \beta_0 + \beta_1 \, \kappa_{it}^{\text{Parent}} + \beta_2 \, \log \, y_{it} + \beta_3 \, \log \, a_{it} + \Gamma \, \text{education}_i + u_{it} \tag{12}$$

This specification is adapted from Zhao and Cui (2021), who investigate the relationship between parents' and children's risk taking in portfolio allocation. In determining the risky share of parents' and children's assets, we follow their approach and define risky share as the sum of investments in stocks and annuity/IRA accounts as a fraction of all liquid assets.[11]

While Zhao and Cui (2021) estimate their regression at the time a child leaves their parent's household and becomes the head of a new household, we estimate the regression based on the years in which the child is between 30 and 35 years old in order to capture the period where equity investments increase sharply and to ensure a sufficiently large sample size. The PSID's FIMS contains information on both biological and adoptive parents when applicable. In constructing the wealth dataset, we consider all parents present in the data. Table 2 presents the results obtained using Specification 12. As in Zhao and Cui (2021), we obtain a significant and positive coefficient on parental risky share, indicating a positive relationship between parents' and children's holdings of risky assets.

Second, we simulate our economy with different values of ψ and estimate Equation 12 on the simulated data. We then choose the ψ value for which the coefficient on the parental

[11] Liquid assets are defined as holdings in stocks, annuity/IRA, bonds/insurance, certificates of deposit, and assets held in checking and savings accounts.

risky share best matches the coefficient in Table 2. Targeting the regression coefficient (β_1 in Equation 12) as opposed to the simple correlation allows us to better isolate the transfer of financial knowledge, removing confounding factors such as education levels, which are also correlated across generations. The result of the calibration process is discussed in Section 5 below.

Table 2: Results of the wealth regression using PSID data.

Variable	**Coefficient**	**Std. Error**
(Intercept)	-0.2906	(0.1765)
Risky Share Parents	0.0926**	(0.0340)
High School (1 = Yes)	0.0252	(0.0526)
College (1 = Yes)	0.0234	(0.0515)
Labor Income (log)	-0.0380**	(0.0171)
Liquid Wealth (log)	0.1077***	(0.0073)

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

While this approach yields useful results, the coefficient on parental risky share is likely to be overestimated due to a number of factors, leading to an overestimated value for ψ.

First, the intergenerational correlation in risky share is likely affected by parental wealth. Children may see wealthy parents as a source of insurance against bad stock market outcomes, increasing their appetite for risk. Children of wealthy parents may also receive financial support that allows them to consider a longer time horizon when investing, justifying riskier investments.

Second, demographic and behavioral factors may also affect the relationship between generations' financial behavior. For example, parents and children are likely to live in areas with similar levels of urbanicity, which could affect asset allocation decisions. Behavioral factors such as risk aversion may also be passed down from parents to children. Further, it could be the case that children mimic their parents' investing behavior, leading to a correlation among risky asset holdings without necessarily impacting the child's financial knowledge.

As we cannot control for factors in our regression that do not exist in our model, we rule out the consideration of demographic and behavioral factors in our regression. While controlling for parental wealth in our regression is possible, it is also futile, as we consider children aged 30–35. In our model, these agents cannot yet have received a bequest by

construction, so the only correlation between the agent's financial behavior and their parent's wealth comes through links in education, which we include in the specification.

Nevertheless, this strategy allows us to benchmark a possible value for ψ under the understanding that it is likely an overestimation.

Table 3: Parameter values in Model 1.

Parameter	Value	Source	Explanation
		Preference Parameters	
γ	5.0	*	Relative risk aversion
β	0.96	Lusardi et al. (2017)	Discount factor
θ_1	$9,000$	*	Strength of bequest motive
θ_2	$100,000$	*	Threshold of bequest motive
		Income Parameters	
$k_\alpha(t)$		†	Age polynomial for labor income
ρ	0.95	Lusardi et al. (2017)	Autocorrelation coefficient for z_t
σ_η	$\sqrt{0.0166}$	Storesletten et al. (2004)	SD of η_t (shock to z_t)
σ_ϵ	$\sqrt{0.0630}$	Storesletten et al. (2004)	SD of income shock
$B_{<HS}$	0.75	Lusardi et al. (2017)	Replacement rate for $< HS$
B_{HS}	0.74	Lusardi et al. (2017)	Replacement rate for HS
B_{C+}	0.63	Lusardi et al. (2017)	Replacement rate for $C+$
		Financial Parameters	
c_d	150.0	*	Stock market participation cost
π_0	500.0	*	Productivity of cost $\pi(i)$
π_1	1.75	Lusardi et al. (2017)	Curvature of cost $\pi(i)$
δ_f	0.06	Lusardi et al. (2017)	Per period depreciation of f
ψ	0.66	*	Inheritance of f
$\bar{r}$	0.02	Lusardi et al. (2017)	Risk free rate
r_{min}	0.00	Lusardi et al. (2017)	Lowest excess return
r_{max}	0.06	*	Highest excess return
σ_λ	0.157	Cocco et al. (2005)	SD of return shock
		Tax Rates	
τ_c	0.2	De Nardi (2004)	Tax rate on capital income
τ_l	0.197	OECD (2024)	Tax rate on labor income[12]
τ_b	0.1	De Nardi (2004)	Tax rate on bequests

*Internally calibrated moments. † Authors' estimations based on PSID Data (see Section 4.1).

[12]Tax wedge for average married worker in 2023

5 Results and Discussion

We begin the discussion of the results by focusing on wealth inequality generated by our main model in comparison to U.S. data retrieved from the PSID. Further, we compare the results from the main specification to several counterfactuals to better understand the dynamics of the model.[13] Table 4 presents key statistics describing the wealth distributions retrieved from the last generation of each simulation.

Table 4: Results for the simulated models.

Wealth	**Share of Wealth in the Top**					**Median**	**Mean**
Gini	1%	5%	20%	40%	60%	**Wealth**	**Wealth**
U.S. Data							
0.80	0.23	0.49	0.80	0.93	0.99	89,200	364,900
Model 1: Bequests and Financial Knowledge							
0.54	0.06	0.22	0.55	0.81	0.92	134,700	239,300
Model 2: No Links in Financial Knowledge							
0.54	0.06	0.22	0.55	0.81	0.92	130,100	232,400
Model 3: Uniform Financial Knowledge							
0.52	0.05	0.2	0.54	0.8	0.92	129,600	220,600
Model 4: No Bequest Motive							
0.51	0.06	0.22	0.55	0.78	0.9	108,400	187,100

U.S. Data from 2021 PSID data. Mean and median wealth in 2015 dollars

5.1 Main Model

The main calibration, Model 1, features multiple mechanisms to model wealth dynamics. Agents endogenously acquire financial knowledge, invest their savings in risky and safe assets, and are linked across generations by bequests, inheritance of financial knowledge and educational attainment probabilities.

Using the process described in Section 4.5, we match the correlation between parents' and children's risky asset shares in the simulation to the same relationship in the U.S. data. Figure 3 shows the path of the regression coefficients over a range of parameter

[13] Table A in Appendix B provides an overview of the parameters used in the main and counterfactual models.

values for ψ. Using $\psi = 0.66$, we match the parent-child risky share correlation of 0.093 near perfectly.

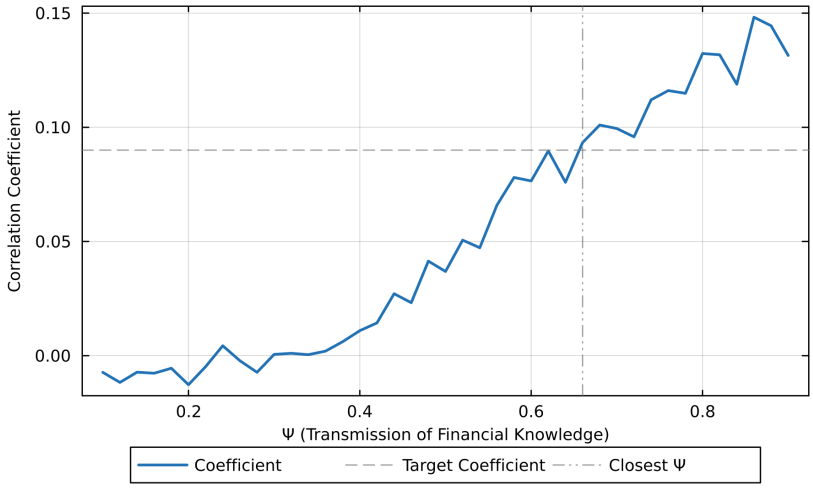
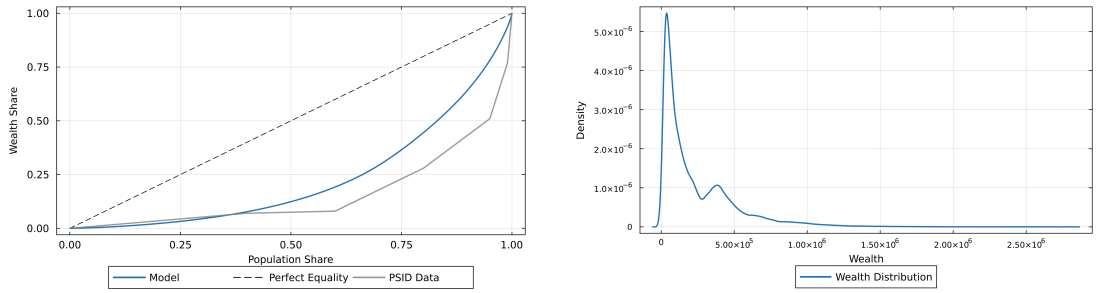


Figure 3: Calibration of the inherited portion of financial knowledge (ψ).

Comparing the simulation results to U.S. data in Table 4, we observe that the wealth inequality generated by our model is significantly lower, resulting in a Gini coefficient on wealth[14] of 0.54, compared to the Gini of 0.80 computed from the U.S. data. The same pattern is observed when considering the wealth held by the top percentiles of the wealth distributions: Our simulations substantially underestimate the wealth held by the top one percent by 17 percentage points. The top 5, 20, 40, and 60 percentiles of the wealth distributions are also underestimated, albeit by a decreasing difference to the actual distribution, as illustrated in Figure 4a. This results in a relatively high median wealth of $\$134,700$ ($\$89,200$ in data) and a relatively low mean wealth of $\$293,300$ ($\$364,900$ in data). Figure 4b shows the distribution of wealth in the simulation. The distribution exhibits a long right tail, though it is not pronounced enough to match the wealth distribution in the PSID data.

[14] In this study, the terms "Gini coefficient" and "Gini index" refer to the Gini coefficient on wealth unless otherwise specified. See Appendix B for the Gini methodology.



(a) Lorenz Curve **(b)** Wealth Distribution

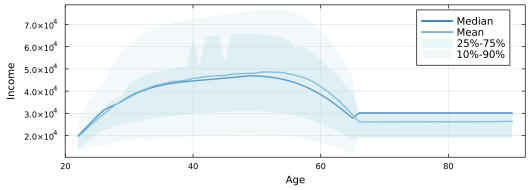
Figure 4: Lorenz curve and wealth distribution for the main calibration.

While the model has difficulties producing a good match for the upper tail of the wealth distribution, it succeeds in producing realistic life cycle paths for key variables. Figure 5 illustrates the life cycle paths for income, wealth, financial knowledge, portfolio allocation, and consumption. The labor income process described in Equation 8 results in a hump shaped income profile, with increasing dispersion until shortly before retirement. Following retirement, agents earn a fixed pension free of shocks (Figure 5a).

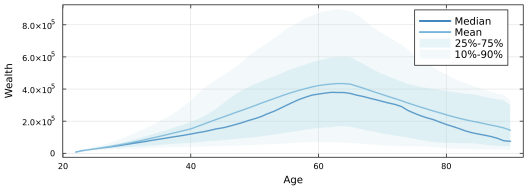
The wealth path also follows a hump-shaped profile: agents enter the model without wealth, and in early periods, they accumulate wealth primarily through saved labor income. With age, agents' wealth paths diverge for a number of reasons. Up to age 40, the dispersion is primarily attributed to differences in labor income and heterogeneous returns to savings. As agents surpass the age of 40, their parents retire and face positive probabilities of death, and the dispersion in wealth is magnified by the added effect of bequests. Once agents reach retirement and incomes are more uniformly distributed, the cross-sectional distribution of wealth declines again (Figure 5b).

Agents acquire financial knowledge gradually throughout their lifetime until retirement, at which point their financial knowledge declines by construction (Figure 5c). Agents also allocate a high share of their savings to risky assets during the early stages of their working lives, which reaches a peak around age 40 and decreases thereafter (Figure 5d). This behavior can be attributed to increased salience of the bequest motive and lower levels of financial knowledge during the later stages of life. Moreover, since labor income and stock market shocks are uncorrelated in our model, young agents' high stock of expected future labor income acts as insurance and allows them to take on more financial risk.

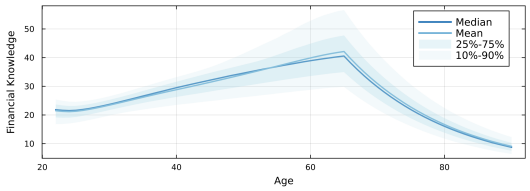
Consumption, while hump shaped, increases only slightly over an agent's lifetime. Cross-sectional variation in consumption increases by the time the first agents receive bequests. Agents smooth their consumption relatively well, though there are discontinuities around the age of retirement and at the end of life (Figure 5e).



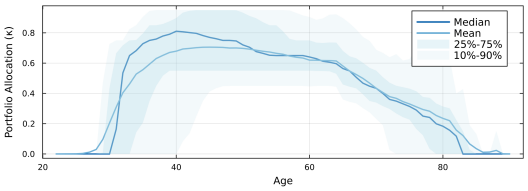
(a) Income ($)



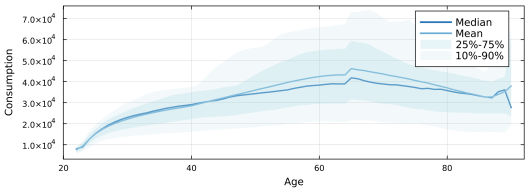
(b) Wealth ($)



(c) Financial Knowledge



(d) Portfolio Allocation



(e) Consumption ($)

Figure 5: Simulated life cycle paths of the main model using $\gamma = 5$, $\theta_1 = 9,000$, $\theta_2 = 100,000$, $\pi_0 = 500$, $c_d = 150$.

Bequests contribute to the wealth accumulation process by generating dynastic effects in the simulation. Figure 6 illustrates the distribution of bequest size left for the next generation. We observe that a large number of individuals receive small bequests, and the bequest distribution has a long but thin right tail. Approximately 31% of agents receive no bequest, with the mean estate being $\$172,000$, over twice the median of $\$81,000$. Moreover, the distribution of bequests is highly varied, with a standard deviation of $\$214,188$.

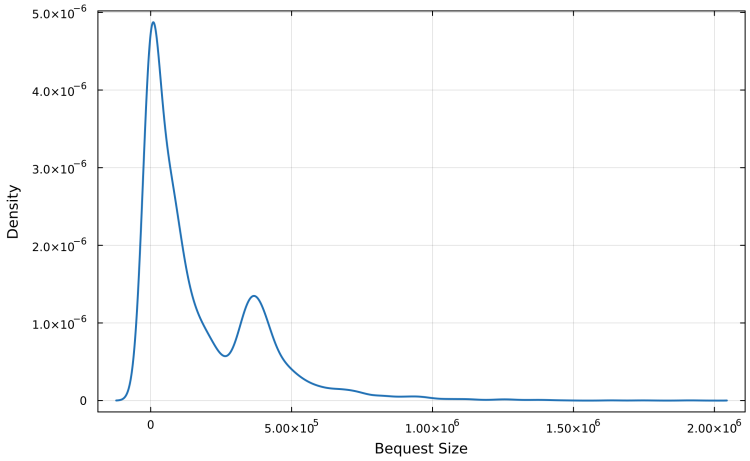
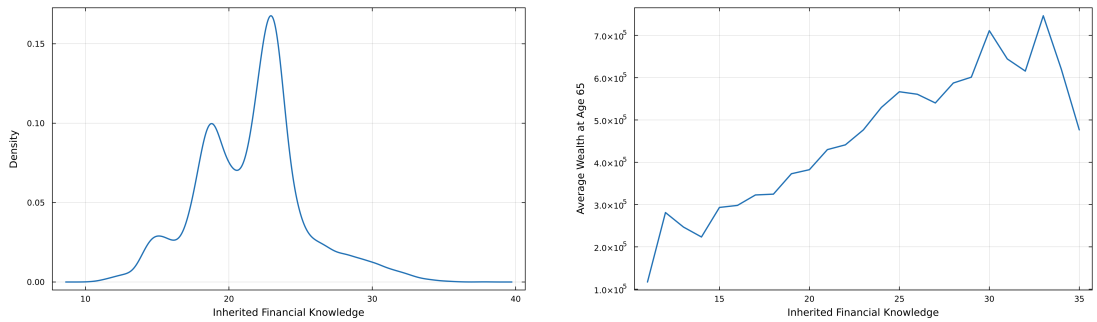


Figure 6: Distribution of the bequests size.

5.2 Counterfactual Models

We present three additional models in order to better understand the impacts of financial knowledge transmission, heterogeneity in financial knowledge, and the bequest motive in Model 1. An overview of the parameters adjusted to achieve each specification is presented in Appendix B.2.



(a) Distribution of inherited financial knowledge

(b) Wealth at retirement by inherited financial knowledge ($)

Figure 7: Distribution and effects of inherited financial knowledge in Model 1.

In Model 2, we remove the inherited component of financial knowledge by setting $\psi = 0$. When all agents start life with zero financial knowledge, we see that inequality remains almost identical to that of the main model. This is because there is generally little variance in financial knowledge in the main model, including at age 46, when the parent's

financial knowledge is measured for the bequest to the child, who has just entered the model at age 22. Thus, no child receives significantly more or less than others: in Model 1, 93% of agents inherit between 15 and 30 financial knowledge points, with a minimum of 10.5 and a maximum of 38, see Figure 7a. However, this model differs from the main model in an important way: agents in Model 2 begin participating in the stock market a few years later in life. This is because there is a positive correlation between a young agent's financial knowledge and their share of risky asset holdings, as shown in Figure 8. This indicates that in a model with more variance in inherited financial knowledge, there would be a large disparity in the age at which agents begin participating in the stock market, leading to larger differences in lifetime capital income and higher inequality.

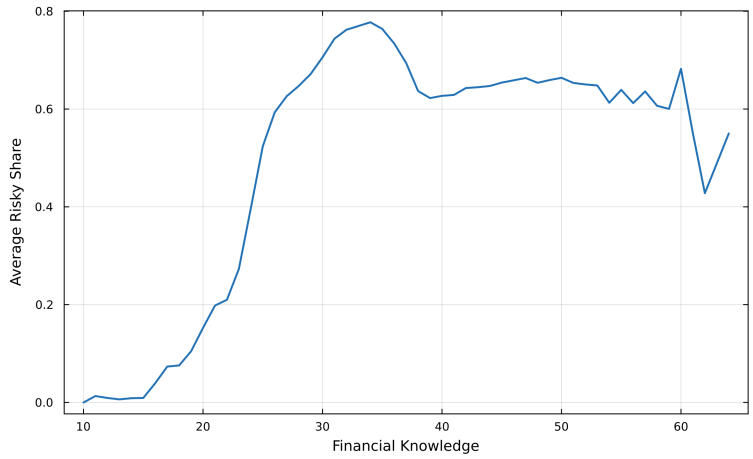


Figure 8: Average risky share by financial knowledge in Model 1, ages 22–30.

In Model 3, all agents are exogenously given the mean financial knowledge ($f = 28$) from Model 1 with no depreciation or ability to acquire more knowledge. This corresponds to a model in which all agents have perfect financial knowledge and the excess return from the stock market is $r(28) = 0.0168$. With heterogeneity in financial knowledge removed, inequality in the model falls slightly, with the Gini coefficient falling from 0.54 to 0.52. This model also generates lower wealth than the baseline, likely driven by reduced capital income between ages 40 and 65, when average financial knowledge in the main model is above 28 and average wealth is high. These results indicate that our model of endogenous financial accumulation does impact inequality, though the effects are again small, in part due to the low variance in f levels.

Finally, Model 4 removes the bequest motive present in Model 1. In this setting, all bequests left are accidental and thus smaller in size with a mean of $\$89,000$ and median

of $\$65,000$ (compared to a mean of $\$172,000$ and a median of $\$81,000$ in the main model), and agents start dissaving significantly around the time that they retire and begin to face a mortality risk. This model produces the largest drop in inequality and wealth relative to the main model, with a Gini coefficient of 0.51 and a median wealth of \$108,400. This shows that the bequest motive is an important driver of wealth accumulation in our setting and that bequests also drive inequality.

5.3 Interpretation

It is not surprising that our model does not replicate the levels of wealth inequality seen in the data. Current literature suggests that generating the ultra-wealthy agents needed to see high wealth concentration among the top one percent requires modeling factors such as entrepreneurship (see Section 2.1). Indeed, the maximum wealth generated in our model is \$3.3 million, compared to approximately \$100 million in the PSID dataset. Nonetheless, our model still falls short of the levels of inequality reported in other studies that do not model these factors, such as De Nardi (2004). Several factors may help explain this shortfall.

First, we may not have calibrated bequests to be a luxury good to a sufficient extent. This explains why the difference in Gini coefficients between our main model and the no bequest motive case is smaller than in De Nardi (2004) (0.03 compared to 0.06). However, even our no bequest motive model yields less inequality than De Nardi's, so does not explain the full difference observed inequalities.

Second, we significantly underestimate income inequality in our model. The simulated data have a Gini index on income of 0.29 compared to roughly 0.41 in U.S. data. In addition to the wealth inequality generated directly by high variance in incomes, increasing income inequality in our model would likely lead to higher variance in financial knowledge, which could generate further inequality. This is supported by the fact that in our model, there are large differences in financial knowledge among different education groups, which differ only in the level and shape of their income paths (see Figure 9).

Third, as we do not model inter vivos transfers, inequality at early ages is significantly lower than the data suggest. It may be the case that the heterogeneity we introduce in the remaining periods simply cannot overcome this initial equality.

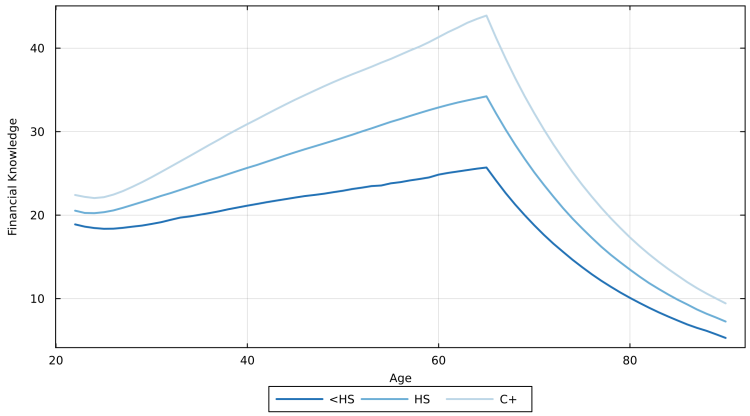


Figure 9: Average financial knowledge by age and education.

Finally, it is possible that inequality is reduced by an overestimation of stock market participation and financial knowledge acquisition among the poor. While Lusardi et al. (2017) find that some agents optimally do not invest in their financial knowledge, we find that all agents in our simulation invest in their financial knowledge and have $f_t > 0$ in all periods. Even in Model 2, where no financial knowledge is inherited, all agents accumulate at least 16 financial knowledge points at some point during their lifetime. Further, we overestimate stock market participation rates in our main model by approximately 28 percentage points compared to a target of 53% in Cupák et al. (2022). In sum, our poorer agents likely earn higher returns on their savings than expected in the real world, increasing wealth at the bottom of the wealth distribution and decreasing wealth inequality.

Despite the low inequality generated by our model, we still find that endogenous financial knowledge accumulation is a useful tool for understanding and modeling wealth inequality. As discussed, our model with financial knowledge accumulation increased wealth inequality over the uniform financial knowledge case (Model 3). In a model with more heterogeneity, this effect could be further compounded through interactions with factors such as labor productivity and bequests.

Moreover, we find that intergenerational links in financial knowledge are also important to explaining wealth inequality. Inherited financial knowledge affects lifetime capital income and wealth (see Figure 7b) through both participation in the stock market and average excess returns. In a setting such as Lusardi et al. (2017)'s with more heterogene-

ity in financial knowledge, the effect of this inherited share on inequality would likely be significantly larger.

5.4 Limitations

This study has a number of limitations that should be acknowledged. First, the solution method may introduce numerical errors due to two main factors: it relies on value function iteration rather than Euler equation-based time iteration (or comparable methods) and uses a relatively coarse grid in the state space due to computational constraints. Second, while the model aims to match key moments from empirical data, discrepancies remain in both the conditional and unconditional stock market participation rates, highlighting that participating in the risky asset class may be too easy in our model. Third, while the PSID data used in this study contain valuable longitudinal information, other data sources, such as the Survey of Consumer Finances (SCF), may contain more useful information on the upper tail of the wealth distribution. Lastly, while the life cycle paths for most simulated variables look realistic, we note that agents do not fully smooth consumption at the very end of their lives, raising questions about how well agents internalize their bequest motives and mortality.

6 Conclusions

We adapt Lusardi et al. (2017)'s framework of endogenous financial knowledge accumulation to an overlapping generations setting with bequests and intergenerational links in labor productivity. We further allow for a fraction of financial knowledge to be passed down from parents to children. This exercise aims to understand whether and how heterogeneity in financial knowledge (and its inheritance) can explain the wealth inequality seen in the real world, for example in U.S. data.

We find that endogenous financial knowledge accumulation increases inequality in our model modestly in comparison to a counterfactual model with a uniform distribution of financial literacy. While this increase in inequality is not driven by the inheritance of financial knowledge, we find that inherited financial knowledge has implications for lifetime wealth, indicating that it may drive inequality in other settings and models with higher variance in financial literacy.

This study contributes to the existing body of literature on wealth inequality and financial knowledge by being one of the first studies to implement a financial knowledge acquisition framework of this type to an overlapping generations setting. Further, to our

knowledge, we are the first to model the inheritance of financial knowledge as a potential source of wealth inequality.

Although this study does not directly intend to explore potential policies, some of the results may be valuable for informing policy that aims to reduce wealth inequality through financial education. We find that early-life financial literacy is important for lifetime wealth, implying that interventions that increase financial literacy among young people could be highly effective in increasing their lifetime savings. If young people's financial knowledge is a function of their parents' financial literacy as in our model, this could further help target financial literacy programs to those who would benefit the most.

The results of this study raise a number of interesting questions for further research. First, both the costs and the intergenerational transmission of financial knowledge are modeled in a simple framework. Models taking into consideration differences in the cost of acquiring financial knowledge based on different demographic factors (e.g., education) could enrich this framework. Furthermore, employing a more accurate mechanism for the intergenerational transmission of financial knowledge may yield valuable insights for potential policies relating to reducing inequality. Lastly, endogenous financial knowledge accumulation could be used to enrich other models of wealth inequality, such as those including entrepreneurship and medical expense risk.

References

Aladangady, Aditya, Jesse Bricker, Andrew C. Chang, Sarena Goodman, Jacob Krimmel, Kevin B. Moore, Sarah Reber, Alice Henriques Volz, and Richard A. Windle (2023). *Changes in U.S. Family Finances from 2019 to 2022: Evidence from the Survey of Consumer Finances*. Tech. rep. Board of Governors of the Federal Reserve System.

Benhabib, Jess, Alberto Bisin, and Ricardo T Fernholz (2022). "Heterogeneous Dynasties and Long-Run Mobility". In: *The Economic Journal (London)* 132.643, pp. 906–925.

Benhabib, Jess, Alberto Bisin, and Shenghao Zhu (2011). "The Distribution of Wealth and Fiscal Policy in Economies with Finitely Lived Agents". In: *Econometrica* 79.1, pp. 123–157.

Cagetti, Marco and Mariacristina De Nardi (2006). "Entrepreneurship, Frictions, and Wealth". In: *The Journal of Political Economy* 114.5, pp. 835–870.

Clark, Robert, Annamaria Lusardi, and Olivia S. Mitchell (2017). "Financial Knowledge and 401(k) Investment Performance: A Case Study". In: *Journal of Pension Economics & Finance* 16.3, pp. 324–347.

Cocco, João F., Francisco J. Gomes, and Pascal J. Maenhout (2005). "Consumption and Portfolio Choice Over the Life Cycle". In: *The Review of Financial Studies* 18.2, pp. 491–533.

Cupák, Andrej, Pirmin Fessler, Joanne W. Hsu, and Piotr R. Paradowski (2022). "Investor Confidence and High Financial Literacy Jointly Shape Investments in Risky Assets". In: *Economic Modelling* 116.

De Nardi, Mariacristina (2004). "Wealth Inequality and Intergenerational Links". In: *The Review of Economic Studies* 71.3, pp. 743–768.

De Nardi, Mariacristina, Eric French, and John Bailey Jones (2009). *Why do the Elderly Save? The Role of Medical Expenses*. Working Paper 15149. National Bureau of Economic Research. URL: http://www.nber.org/papers/w15149.

Duvall, James (2021). *Trends in the Expenses and Fees of Funds, 2020*. ICI Research Perspective 27, no. 3. Accessed: 2025-05-09. Investment Company Institute. URL: https://www.ici.org/doc-server/pdf%3Aper27-03.pdf.

Horowitz, Juliana Menasce, Ruth Igielnik, and Rakesh Kochhar (2020). *Trends in Income and Wealth Inequality*. Washington, DC: Pew Research Center. URL: https://www.pewresearch.org/social-trends/2020/01/09/trends-in-income-and-wealth-inequality/.

Huggett, Mark, Gustavo Ventura, and Amir Yaron (2011). "Sources of Lifetime Inequality". In: *The American Economic Review* 101.7, pp. 2923–2954.

Keane, Michael P. and Kenneth I. Wolpin (1997). "The Career Decisions of Young Men". In: *The Journal of Political Economy* 105.3, pp. 473–522.

Kent, Ana Hernández (2025). *The State of U.S. Household Wealth*. Tech. rep. Accessed: 2025-03-29. Federal Reserve Bank of St. Louis. URL: https://www.stlouisfed.org/community-development/publications/the-state-of-us-household-wealth.

Kim, Min (2024). *Financial Literacy, Portfolio Choice, and Wealth Inequality: A General Equilibrium Approach*. Working Paper WP2024-4. Wharton Pension Research Council.

Klapper, Leora, Annamaria Lusardi, and Peter van Oudheusden (2015). *Financial Literacy Around the World: Insights from the S&P Global FinLit Survey*. Tech. rep. Global Financial Literacy Excellence Center (GFLEC), The George Washington University School of Business; The World Bank. URL: https://gflec.org/wp-content/uploads/2015/11/Finlit_paper_16_F2_singles.pdf.

Kopecky, Karen A. and Richard M.H. Suen (2010). "Finite State Markov-Chain Approximations to Highly Persistent Processes". In: *Review of Economic Dynamics* 13.3, pp. 701–714.

Lockwood, Lee M. (2012). "Bequest Motives and the Annuity Puzzle". In: *Review of Economic Dynamics* 15.2, pp. 226–243.

Lusardi, Annamaria and Carlo de Bassa Scheresberg (2013). *Financial Literacy and High-Cost Borrowing in the United States*. Working Paper 2013-1. Global Financial Literacy Excellence Center.

Lusardi, Annamaria, Pierre-Carl Michaud, and Olivia S. Mitchell (2015). *Using a Life Cycle Model to Evaluate Financial Literacy Program Effectiveness*. CIRANO Working Papers 2015s-14. CIRANO. URL: https://ideas.repec.org/p/cir/cirwor/2015s-14.html.

– (2017). "Optimal Financial Knowledge and Wealth Inequality". In: *The Journal of Political Economy* 125.2, pp. 431–477.

Lusardi, Annamaria and Olivia S Mitchell (2011). *Financial Literacy and Retirement Planning in the United States*. Working Paper 17108. National Bureau of Economic Research. URL: http://www.nber.org/papers/w17108.

Lusardi, Annamaria and Peter Tufano (2015). "Debt Literacy, Financial Experiences, and Overindebtedness". In: *Journal of Pension Economics and Finance* 14.4, pp. 332–368.

National Center for Health Statistics (2025). *United States Life Tables*. Centers for Disease Control and Prevention. Data retrieved in 2025. URL: https://www.cdc.gov/nchs/nvss/life-expectancy.htm.

OECD (2024). *Taxing Wages- the United States*. Accessed: April 3, 2025. URL: https://www.oecd.org/content/dam/oecd/en/topics/policy-issues/tax-policy/taxing-wages-united-states.pdf.

Panel Study of Income Dynamics (2025). *Panel Study of Income Dynamics, Public Use Dataset*. Produced and Distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI. URL: https://psidonline.isr.umich.edu/.

Quadrini, Vincenzo and José-Víctor Ríos-Rull (1997). "Understanding the U.S. Distribution of Wealth". In: *Federal Reserve Bank of Minneapolis Quarterly Review* 21.2, pp. 22–36.

Robinhood Markets, Inc. (2025). *Robinhood Gold*. Accessed: 2025-04-24. URL: https://robinhood.com/us/en/gold/.

Saez, Emmanuel and Gabriel Zucman (2016). "Wealth Inequality in the United States Since 1913: Evidence from Capitalized Income Tax Data". In: *The Quarterly Journal of Economics* 131.2, pp. 519–578.

Stango, Victor and Jonathan Zinman (2009). "Exponential Growth Bias and Household Finance". In: *The Journal of Finance* 64.6, pp. 2807–2849.

Storesletten, Kjetil, Christopher I. Telmer, and Amir Yaron (2004). "Consumption and Risk Sharing over the Life Cycle". In: *Journal of Monetary Economics* 51.3, pp. 609–633.

Tang, Ning, Olivia S. Mitchell, Gary R. Mottola, and Stephen P. Utkus (2010). "The Efficiency of Sponsor and Participant Portfolio Choices in 401(k) Plans". In: *Journal of Public Economics* 94.11, pp. 1073–1085.

U.S. Securities and Exchange Commission (2024). *SEC Adopts Rules to Amend Minimum Pricing Increments and Access Fee Caps and to Enhance the Transparency of Better Priced Orders*. Press Release No. 2024-137. URL: https://www.sec.gov/newsroom/press-releases/2024-137.

Urban, Carly and Olivia Valdes (2022). *Why Is Measured Financial Literacy Declining and What Does It Mean? Maybe We Just "Don't Know."* Tech. rep. FINRA Investor Education Foundation. URL: https://finrafoundation.org/sites/finrafoundation/files/2024-10/Why-Is-Measured-Financial-Literacy-Declining.pdf.

Vanguard Group Inc (2025). *Low-Cost, No-Load Funds Are Just The Start*. Accessed: 2025-04-24. URL: https://investor.vanguard.com/investor-resources-education/mutual-funds/no-load-funds.

Vissing-Jorgensen, Annette (2003). "Perspectives on Behavioral Finance: Does 'Irrationality' Disappear with Wealth? Evidence from Expectations and Actions". In: *NBER Macroeconomics Annual* 18, pp. 139–194.

World Inequality Database (2025). *Share of Wealth Held by Top 1% in the United States*. Accessed: 2025-03-29. URL: https://wid.world/country/usa/.

Yakoboski, Paul J., Annamaria Lusardi, and Andrea Sticha (2024). *Financial Literacy and Retirement Fluency: New Insights for Improving Financial Well-being*. Tech. rep. TIAA Institute and Global Financial Literacy Excellence Center (GFLEC). URL: https://gflec.org/wp-content/uploads/2024/04/TIAA_GFLEC_Report_PFin_April2024_07.pdf.

Zhao, Ziwei and Min Cui (2021). "Investing Like My Parents: Do Parents Affect Children's Risk Taking Behavior?" In: *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI - ESSEC*.

A Appendix - Data

We utilize data from the Panel Study of Income Dynamics (2025), a longitudinal household survey conducted by the Survey Research Center at the University of Michigan. We base the data for this study on two main components of the PSID.

We consider the family files in the time period from 1984–2019 using both the SRC (Survey Research Center) and SEO (Survey of Economic Opportunity) samples to better represent the full income distribution. We extract information on educational attainment, labor income, age, and family composition. Within the samples, we consider household heads aged between 22–90. To eliminate potential sampling bias, we apply the appropriate weights.

For the wealth files, we consider data from 1999 to 2021 to extract information on liquid asset holdings (i.e., checking and savings accounts, certificates of deposit, government bonds and bills), stock holdings including mutual funds, retirement accounts (i.e., IRAs and annuities), and total wealth.

For all monetary variables extracted from the PSID, we inflation adjust to 2015 U.S. dollars using the Consumer Price Index (CPI).

B Appendix - Formulas and Extensions

B.1 Gini Index Calculations

The Gini coefficient in this paper is calculated using the standard mean difference formula:

$$\text{Gini} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2n \sum_{i=1}^{n} x_i} \tag{A}$$

where x_i represents the wealth of individual i and n is the total number of individuals in the distribution. This implementation computes the arithmetic mean of the absolute differences between all pairs of observations, divided by twice the mean of the distribution. The coefficient ranges from 0 (perfect equality) to 1 (perfect inequality).

B.2 Parameter Overview

Table A: Overview of parameter variations for the main and counterfactual models

Parameter	Model 1	Model 2	Model 3	Model 4
θ_1	9000.0	9000.0	9000.0	0.00
r_{max}	0.06	0.06	0.0168	0.06
δ	0.06	0.06	0.00	0.06
π_0	500.0	500.0	0.01	500.0
ψ	0.66	0.00	0.00	0.66

Model 1: Bequests and endogenous financial knowledge, **Model 2:** No links in financial knowledge, **Model 3:** Uniform financial knowledge, **Model 4:** No bequest motive. Blue text indicates parameter variations to Model 1.