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# Breaking the Dynastic Cycle: Inequality, Taxation, and Redistribution

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**Abstract**

This paper studies the long-run distributional effects of inheritance taxation and redistribution within an agent-based overlapping-generations model featuring heterogeneous agents who differ in demographics, returns to wealth, education, and consumption behaviour. The results show that progressive inheritance taxation combined with redistribution substantially reduces wealth inequality, while consumption inequality declines more gradually and with a delay. This lag reflects lifecycle dynamics: younger households predominantly save transfers, whereas middle-aged households consume at peak earning stages. Importantly, these policies do not erode aggregate wealth. Instead, they reallocate wealth across households without shrinking the total wealth stock. The top 1% and top 10% experience losses in both wealth shares and absolute wealth levels, while the bottom 50% gain in both dimensions. These effects intensify over time and become particularly pronounced after several decades, as redistribution translates into higher human capital accumulation and improved lifetime earnings for lower-wealth households. Overall, the findings suggest that the conventional equity–efficiency trade-off is significantly weakened when tax revenues operate as a form of pre-distribution rather than mere ex post redistribution. In this framework, the true efficiency loss stems not from taxation, but from the long-run compounding of dynastic wealth concentration under policy inaction.

**JEL Class.:** C63, D31, H23, J11

**Keywords:** Intergenerational Transmission, Wealth Inequality, Agent-Based Model, Overlapping Generations, Inheritance taxation, Redistribution

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# Breaking the Dynastic Cycle: Inequality, Taxation, and Redistribution†

*Ismaila Y. Jammeh, Federico Giri and Alberto Russo*

## 1 Introduction

Inequality hampers long-term economic growth (Caiani, Russo, & Gallegati, 2019; Galor & Zeira, 1993; Stiglitz, 2015), distorts public policy, and reduces social mobility. When resources are distributed unevenly, intergenerational disparities tend to persist and, in many cases, intensify over time. This paper examines a key mechanism driving the persistence and amplification of inequality across generations: the intergenerational transfer of wealth. More specifically, we investigate the long-term effects of inheritance taxation and redistributive policies as potential instruments to counteract this dynamic.

Intergenerational wealth transfer is at the nexus of economics, sociology, and political philosophy. It concerns the process by which economic advantage or disadvantage is passed from one generation to the next, not through merit or labour, but through the accident of birth. This process is a powerful force in shaping the economic landscape of societies, influencing everything from individual life chances to aggregate macroeconomic performance. The core question is whether inherited wealth serves as a foundation for productive capital accumulation or as a cornerstone of entrenched self-perpetuating dynasties.

This study was motivated by two factors. First, there is a growing recognition that the traditional notion of a "*rising tides lift all boats*" (King, 2017; Stiglitz, 2016), which assumes that wealth concentration among the rich, when invested, eventually benefits everyone, is increasingly tenuous. In reality, extreme wealth concentration often begets inequality of opportunity, where children from affluent households obtain superior education, social networks, and, particularly, substantial financial transfers (Adermon, Lindahl, & Waldenström, 2018; Chetty, Hendren, Kline, Saez, & Turner, 2014; Nordblom & Ohlsson, 2011; Szydlik, 2004). This creates a cycle in which the inequality of outcomes in one generation fuels the inequality of opportunities in the next. This is evidence from the recent studies that employed administrative data by linking surnames, found that intergenerational persistence persists after several generations-elite families centuries ago still maintain their elite status (Barone & Mocetti, 2021; Bourdieu,

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Kesztenbaum, Postel-Vinay, & Suwa-Eisenmann, 2019; Hao, 2021; Shiue, 2025).

Secondly, we are currently experiencing an unprecedented "Great Wealth Transfer," as highlighted by data from the Survey of Consumer Finance. The baby-boom generation, which emerged after World War II, has accumulated substantial wealth, and this wealth is now being transferred to its heirs. The scale of this transfer has sparked urgent discussions about the role of policy in managing its distributional effects, making the examination of inheritance taxation particularly timely and essential in today's context. This brings us to the role of redistributional policies-how these inheritance taxes can be used to promote social welfare and increase social mobility.

That said, standard macroeconomic models often assume constant and homogeneous demographics across households (Aksoy, Basso, Smith, & Grasl, 2019; Blanchard, 1985; Zagheni & Wagner, 2015). Demographic factors such as fertility and mortality shape both the timing and magnitude of transfers that heirs receive upon the death of a testator. Household size further determines how much households consume and save as they accumulate wealth for bequests. The longer a testator lives, the later heirs will receive their inheritance; and with life-cycle consumption smoothing, a testator who survives into retirement is likely to draw down wealth through rising expenditures, reducing what can ultimately be passed on. Household size also governs how inheritance is divided among heirs – those from smaller households will each receive a larger share than heirs from larger ones, assuming equal levels of accumulated wealth.

Most importantly, these earlier frameworks abstract from intergenerational dynasties, for instance, in the framework of Blanchard (1985), wealth left by an individual is distributed among all surviving individuals rather than solely to the deceased's heirs (no dynasties). These assumptions are often employed to avoid modelling family connections and to maintain consistency in aggregate assets. Although this framework is an improvement over the classical model, where wealth disappears upon an individual's death, it eventually leads to a decline in aggregate capital. This class of models cannot account for the intergenerational persistence observed within families and dynasties. Therefore, to examine the intergenerational transmission of wealth across households, we tracked individuals within the same lineage to redistribute the wealth of the deceased within their lineage. This approach helps examine how wealth transfer can shed light on intergenerational persistence and how policies such as inheritance taxation and government redistribution can help reduce the intergenerational persistence and promote social mobility.

From a long-term perspective, the role of inheritance taxation and redistribution is not merely to generate government revenue in a single fiscal period. Rather, it is a fundamental tool for intervening in the dynastic cycle of wealth accumulation and redistribution. As the seminal work by Piketty (2014) and others has shown, when the rate of return on capital ($r$) exceeds the economic growth rate ($g$), wealth accumulated in the past grows faster than output and wages. This dynamic inherently privileges inherited wealth over earned income, potentially leading economies toward a *"patrimonial capitalism"* reminiscent of the $19th$ century. In this context, inheritance taxation acts as a corrective mechanism that slows the compounding of dynastic wealth across generations. The long-term impact of inheritance is dynamic and complex. Recent empirical evidence, such as the study by Nekoei and Seim (2023) in Sweden, reveals that inheritances can have a dual effect: they may compress relative wealth inequality in the short run by boosting the wealth of poorer heirs proportionally more, but they widen it in the long run as wealthy heirs preserve and invest their windfalls while less wealthy heirs consume theirs; this is true in Great Britain and other European and developed countries (Karagiannaki, 2017; Morelli, Nolan, Palomino, & Van Kerm, 2025). This underscores that a snapshot analysis is insufficient; a multigenerational view will allow us to examine the intergenerational compounding impact of household wealth.

Therefore, this study positions inheritance taxation and the strategic redistribution of its proceeds, for instance, into broad-based educational investment, not just as a tool of redistribution, but of predistribution (Cowell, Van De Gaer, & He, 2018). By curbing the largest concentrations of inherited wealth and simultaneously enhancing human capital and opportunities for those from less wealthy backgrounds, such policies can help level the playing field across generations and increase social mobility. It addresses inequality at its source by moderating the initial endowments individuals bring to the market, as analysed in Galor and Zeira (1993). The central thesis is that a well-designed inheritance tax system, with high exemptions and progressive rates on large estates, can be a powerful instrument to promote equality of opportunity, enhance social mobility, and counteract the self-reinforcing dynamics of wealth inequality over the long term, without necessarily sacrificing economic efficiency.

## 2 Review of the Literature

The intergenerational transfers of advantages, such as the transfer of wealth from parents to their children through inter vivos gifts and/or inheritance plays a crucial role in the persistence of modern inequality. Households with greater resources can shape institutions and policies to favour their interests, exacerbating existing inequalities (King, 2017), and thus can distort taxes and public spending.

The literature on intergenerational transfers produces different estimates about how much inherited wealth contributes to household wealth accumulation. Early life-cycle models, particularly those advanced by Modigliani (1988), estimated that intergenerational transfers account for about $20\%$ of household wealth, with the remaining stemming from life-cycle savings accumulated during working years to smooth consumption during retirement years—this earlier view positioned inheritance as a relatively modest factor in overall wealth formation. Despite employing the same U.S. data, Kotlikoff and Summers (1981) arrived at different estimates. They estimated that intergenerational transfers actually constitute around $80\%$ on aggregate household wealth. This stark discrepancy in estimates stems largely from methodological differences: The latter capitalised inherited wealth over time, including not only the initial bequest but also the accumulated returns on that wealth. Their approach implies that inherited wealth, rather than earnings from labour, serves as the dominant driver of wealth accumulation. Subsequent studies, such as those by Gale and Scholz (1994), attempted to reconcile these positions by distinguishing between intended transfer (inter vivos gifts and educational expenditures) and unintended transfer (bequests). Their analysis of the U.S. survey data found that inter vivos transfers account for at least $20\%$ of net worth. while bequests contribute an additional $31\%$, suggesting that over half of household wealth can be traced to intergenerational transfer. This finding underscores that both inheritance and lifetime parental support play a crucial role in wealth accumulation.

The differences in estimates across studies reflect the differences in definitions, methodologies, and time periods examined. Modern data increasingly confirm that intergenerational transfers are sizeable, though the truth likely lies between the extreme positions. Piketty and Zucman (2015) comprehensive historical analysis demonstrated that inheritance plays a central role in wealth concentration, documenting a U-shaped pattern in the ratio of private wealth to national income across European countries over century-high in the $18th$ and $19th$ centuries, declining sharply in the mid-$20th$ century due to wars, and rising again from the $1950s$ to historical peaks.

Other empirical studies have shown that inheritances and gifts constitute a substantial share of aggregate wealth (Adermon et al., 2018; Gale & Scholz, 1994; Kotlikoff & Summers, 1981; Nordblom & Ohlsson, 2011; Szydlik, 2004), which is likely over half in many developed countries. While earlier life-cycle models downplayed this Modigliani (1988), more recent data-driven studies and models with bequest motives have reaffirmed that intergenerational transfers are critical to the dynamics of wealth accumulation. Both channels interact; for instance, the expectation of an inheritance may reduce one's savings, as a young heir might save less if they anticipate inheriting a house or portfolio (Karagiannaki, 2017; Nekoei & Seim, 2023). This feedback implies that policy changes, such as introducing or raising an inheritance tax, could influence not only wealth transmission but also life-cycle saving behaviour in complex ways, as people adjust their expectations and motives, or provide support earlier (inter vivos) to avoid paying taxes with the bequests/inheritance channel.

Understanding wealth accumulation requires consideration of why people save. In pure life-cycle models without bequest motives, people save for retirement and against uncertainty. However, precautionary saving in response to uncertain lifespans and imperfect insurance can generate substantial wealth accumulation—Caballero (1991) suggested that earnings uncertainty alone could explain over $60\%$ of U.S. wealth accumulation. Such precautionary wealth, if unconsumed at death, becomes accidental bequests (Abel, 1985), blurring the distinction between life-cycle and transfer wealth. De Nardi (2004) overlapping-generations model incorporating both accidental and voluntary bequests demonstrates that voluntary bequest motives are crucial for generating the extreme wealth concentration observed at the top of the distribution. Accidental bequests alone cannot produce the fortunes of the wealthiest families. Only when households actively save to leave large estates (i.e. a dynastic motive) do we see the emergence of wealth concentration matching real-world top shares. When high earnings ability persists within families, these families earn more and leave larger bequests, further amplifying concentration.

Recent studies have moved beyond measuring the share of inherited wealth to examining its distributional consequences. Nekoei and Seim (2023) from employing Swedish data, reveals a crucial temporal dynamics: inheritances initially reduce relative wealth inequality because inheritances are distributed more broadly than existing wealth, and a given inheritance provides a larger proportional boost to less wealthy households. However, over the longer term, inheritances increase wealth inequality because wealthier heirs invest their inheritances to earn returns while less wealthy heirs tend to deplete theirs. This divergence stems primarily from differential rates of returns rather than differences in consumption or labour supply. This evidence reiterated the study by Karagiannaki (2017) analysis using British data from $1995-2005$ found this behavioural pattern; the study found that approximately $30\%$ of inheritances were spent on average, with wealthier households saving a larger fraction of their inheritances. In contrast to Swedish findings, inheritances during this period did not significantly drive wealth inequality in Britain, largely because housing bubbles and associated housing wealth growth were the dominant factors shaping the wealth distribution. Elinder, Erixson, and Waldenström (2018) using Swedish population-wide study, also found that inheritance reduces relative inequality while increasing absolute dispersion; the dollar gaps between the rich and the poor widen as ratios shrink. This dual effect highlights the importance of measurement choices in assessing inequality impacts. Morelli et al. (2025) cross-country analysis of six wealthy nations (Germany, Spain, France, Italy, Great Britain, and the United States) demonstrates that the size distribution of inheritances significantly determines their inequality effects. Increasing the share of people receiving small or medium inheritances tends to reduce wealth inequality by lifting more households into the middle of the distribution. In contrast, increasing the number of recipients of very large inheritances (typically above the $95th$ percentile) widens inequality. The threshold at which inheritances become inequality-increasing varies across these countries, sometimes aligning with inheritance tax exemption levels and sometimes diverging significantly.

The evidence that inheritance can entrench inequality over generations has focused attention on inheritance taxation as a potential remedy. The debate over inheritance taxation is centered on the equity-efficiency trade-off (Cowell et al., 2018; Piketty & Saez, 2013). Critics argue that inheritance taxation may discourage savings and work effort among those with bequest motives, while potentially inducing costly avoidance strategies through trusts, loopholes or wealth offshoring. Heirs might also reduce work efforts if they anticipate inheritances, the so-called *"Carnegie conjecture"* that inherited wealth saps initiative. In contrast, proponents argue that inherited wealth is unearned by recipients, making its taxation less distortionary than taxing wages. Large inheritances perpetuate inequality of opportunity, and taxing them can help level the playing field, particularly if the revenue funds public education, healthcare, or other social goods. Philosophically, society may legitimately claim a portion of wealth beyond a certain threshold that threatens democracy or meritocratic ideals (Cowell et al., 2018; Galle, Gamage, & Lord, 2025; Piketty & Saez, 2013).

In theory, taxing large fortunes or inheritances can help redistribute resources and level the playing field. However, wealth is often under-taxed, and the wealthiest households frequently avoid paying taxes through sophisticated means, such as offshore tax havens, legal loopholes and unrealised capital gains (Zucman, 2019). There is mixed evidence on the effectiveness of inheritance taxation. Many countries maintain relatively low rates or higher exemptions, meaning only the largest estates face significant taxation. Recent estimates in the United States suggest that the richest households collectively evade between $150$ to $163$ billion in taxes each year, making up a large share of the "tax gap". This tax avoidance by the top $1\%$[1], responsible for a disproportionate share of unpaid taxes, reduces government revenue and limits social expenditures that could mitigate inequality (such as education, healthcare, or poverty alleviation programs). The outcome is lower social mobility, potential underinvestment in public goods, slow economic growth and even higher crime rates.

Optimal tax theory provides frameworks for evaluating inheritance tax design. Piketty and Saez (2013) develops a model balancing equity (the social welfare benefit of redistribution) against efficiency (behavioural responses to taxation). Under reasonable parameter assumptions, they find optimal inheritance tax rates of $50 - 60\%$ or higher for the largest bequests. If bequests are highly elastic to taxation, the optimal rate falls to around $35\%$; if inelastic, it rises to approximately $70\%$. These models generally advocate high exemption thresholds combined with progressive rates targeting only the largest transfers. Cowell et al. (2018) documents a dual role of inheritance taxation: redistribution (after-tax transfers to equalise outcomes) and predistribution (policies improving initial endowment before market outcomes). Funding public education or healthcare from inheritance tax revenues can simultaneously reduce the wealth of the richest heirs and the amount of wealth transferred, while also boosting the human capital and opportunities for the broader population, potentially interrupting the intergenerational transmission of (dis)advantage, and increasing social mobility.

Recent studies of intergenerational mobility employing administrative tax records and linking families through surnames document intergenerational persistence across several centuries apart (Barone & Mocetti, 2021; Clark, 2015; Hao, 2021; Shiue, 2025). These studies have provided evidence of dynastic wealth across many developed and emerging economies, in which elite families that held significant amounts of wealth centuries ago, their descendants still hold a significant amount of wealth, despite centuries apart. In addition, Adermon et al. (2018) also examines intergenerational mobility across four generations in Sweden. This study found that parental wealth and grandparental wealth determine children's and grandchildren's wealth status. Specifically, the parent-child wealth rank correlation is between $0.3 - 0.4$, while the grandparents-grandchild rank correlation falls between $0.1 - 0.2$, which is conditional on parent wealth. However, at least $50\%$ of this correlation stems from bequest and inter vivos gift, while education and earning contributes to $25\%$ of the parent-child wealth correlation.

These recurrent pieces of evidence indicate that adopting a long-term, dynastic perspective will help us understand the role of parental economic status and wealth transfers on intergen-

[1] https://americansfortaxfairness.org/keep-irs-adequately-funded-catch-rich-tax-cheats

erational persistence and mobility and how they drive wealth inequality. Short-term analysis may underestimate the true impact of inheritances, since it compounds over generations, specially, if the transmission is through inter vivo or educational investment-which will take time to influence the outcomes of their children. This is evidence of the divergent estimates on the role of intergenerational transfers on household wealth. A family receiving a modest inheritance across multiple generations will accumulate substantially more wealth than a family receiving none, even if no single transfer appears transformative. Without progressive taxation or exogenous shocks (such as wars), this dynamic can produce self-reinforcing inequality regimes. The observed U-shaped pattern in the evolution of wealth-to-income ratios and inheritance shares in countries like France and the UK illustrates how major shocks (wars, inflation, high taxation) temporarily reduce inherited wealth's importance, only for it to resurge as peacetime conditions return (Alvaredo, Garbinti, & Piketty, 2017; Piketty & Saez, 2014).

Several important gaps remain in the literature. First, the importance of human capital transmission relative to material transfers remains contested. As Cagetti and De Nardi (2008) has demonstrated, human capital is exogenous in all quantitative models of wealth inequality; endogenising it with heterogeneous abilities and shocks will help us replicate data on earnings inequality over the life cycle. In addition, if human capital accumulation is hindered by credit constraints, it will help us to examine how children's family background determines their success before receiving transfers, and thus provide a better understanding of the importance of human capital relative to transfers in generating wealth inequality-this is key to the model of Galor and Zeira (1993), in which the differences in human capital due to unequal access in credit market between the rich and the poor creates inequality and reduces steady-state economic growth. Furthermore, in the spirit of Bowles and Gintis (2001), they argue that education, networks, and values passed from parents to their children may matter more than financial transfers. A child receiving an elite education and connections may achieve a higher wealth status without significant financial inheritance. Disentangling these channels empirically remains challenging,g but crucial in understanding intergenerational persistence.

Secondly, heterogeneous demographic patterns, particularly the age at which heirs receive transfers and family size, introduce substantial variation in both the timing and the amount inherited, a dimension largely overlooked in existing studies. Inheriting wealth at 30 faces a fundamentally different accumulation trajectory than one inheriting at 55 or above, and stochastic mortality can generate sudden surges in inheritance flows that compress or widen inequality in ways that static models cannot capture (Zagheni & Wagner, 2015).

Third, households faces heterogeneities in their economic decision, which are influence by demographic factors (such as household size). Specifically, households at different points of the income and wealth distribution have different consumption patterns. As evidence indicated, marginal propensities differs between the rich and the poor (Dynan, Skinner, & Zeldes, 2004; Kaplan & Violante, 2014). However, the representation agent model cannot account for how households with the same wealth ends up with different savings, due to demographic heterogeneities, which ultimately determines the amount of inheritances their heirs will receive.

Taken together, the literature establishes that intergenerational wealth transfers are large, persistent across multiple generations, and capable of both compressing and widening inequality depending on the time horizon and the distribution of transfers (Elinder et al., 2018; Morelli et al., 2025; Nekoei & Seim, 2023). However, existing models are limited in their ability to capture the full complexity of this process. Representative agent and analytical OLG frameworks abstract from the heterogeneity in demographics, returns, consumption, and human capital that drives the dynastic dynamics documented in the empirical record (Cagetti & De Nardi, 2008). Short-run analyses miss the compounding effects that only materialise across generations, while models without endogenous human capital cannot capture the predistributive channel through which inheritance taxation can alter the starting conditions of the poor.

To address these gaps, this paper brings together the Overlapping Generations (OLG) framework and the Agent-Based (AB) approach (Axtell & Farmer, 2025; Delli Gatti, Fagiolo, Gallegati, Richiardi, & Russo, 2018), developing an AB-OLG model that embeds intergenerational dynamics within a fully heterogeneous microstructure. The model allows for simultaneous heterogeneity in demographic trajectories, returns to wealth, educational attainment, and consumption behavior, while explicitly tracking individuals within the same lineage across multiple generations. By combining life-cycle structure with agent-level interaction and distributional dynamics, this framework makes it possible to capture the cumulative and path-dependent processes through which wealth disparities persist and amplify over time. It is therefore particularly well suited to studying how inheritance taxation and redistributive mechanisms operate within the structural mechanisms of wealth accumulation. In doing so, the model enables a rigorous assessment of whether a carefully designed inheritance tax can disrupt dynastic wealth concentration without undermining aggregate efficiency or long-run growth.

# 3 The model

This section presents the AB-OLG model and its core components. It details the demographic processes (population ageing, fertility, mortality and birth process), the economic behaviours (human capital, earnings, consumption/savings, wealth accumulation and inheritance mechanism), the key behavioural equations linking these elements and the simulation design and algorithm.

## 3.1 Demographic Behaviours

The demographic module incorporates four overlapping generations: parent, first, second and third generations. Individuals of one generation give birth to those in the next generation, respectively. By assigning an ID to each individual, and the ID's of their parent, grandparent and great-grandparent, we are able to track wealth transmission across individuals in the same lineage.

Moreover, given this complex multigenerational tracking, we will use a generic notation to denote individuals across all generations, to minimise the number of behavioural equations.

We let individuals in the initial (parent) generation be indexed as $h = 1, 2, 3, \ldots, H$ and all newborn individuals in the proceeding generations (first, second and third) be indexed as $j = 1, 2, 3, \ldots, J$. Additionally, we denote all individuals in all generations (including the parent generation) as $i = 1, 2, 3, \ldots, N$. These notations will prevent us from defining a behavioural equation for each generation, which will make the deposition of the model framework and its components cumbersome.

### Initial Age Distribution

We start with a fixed number of parent generation individuals $H$ at $t = 1$, disaggregated into cohorts given by:

$$\text{Cohorts}_{t=1} = \begin{cases} \text{young} & \text{if} \quad a_{h,1} \leq 14 \\ \text{working} & \text{if} \quad 15 \leq a_{h,1} \leq 64 \\ \text{retired} & \text{if} \quad a_{h,1} > 64 \end{cases} \tag{1}$$

Each parent's individual $h$ is stored in their generational age matrix $a_{h,t}$, where columns represent period, and rows represent individuals. Thus, the age matrix and the proportion of each cohort at the start of the simulation is given by:

$$a_{h,1} \sim \begin{cases} \text{young} & \text{with} \quad \Pr = p \\ \text{working} & \text{with} \quad \Pr = q \\ \text{retired} & \text{with} \quad \Pr = 1 - p - q. \end{cases} \tag{2}$$

This disaggregation will enable us to examine how the initial age structure affects economic outcomes, the effects of ageing on economic outcomes and the role of redistribution policies, such that we can examine the effects of target redistribution to the retired individuals.

### Survival and Ageing

Agents either survive or die in each period $t$, determined by the Gompertz-Makeham (G-M) mortality law, $\mu(a_{i,t})$, which indicates that an individual dies exponentially with age (Gavrilov & Gavrilova, 2024; Missov, Lenart, Nemeth, Canudas-Romo, & Vaupel, 2015). The G-M function is represented as.

$$\mu(a_{i,t}) = A + \frac{B}{C} \cdot \underbrace{(e^{C \cdot (a_{i,t} + \Delta t)} - e^{C \cdot a_{i,t}})}_{\text{Discrete Forward Difference}} \quad \text{with} \quad \Delta t = 1 \tag{3}$$

The equation $\mu(a_{i,t})$ is a discrete-time mortality hazard that computes the age-dependent mortality of individual $i$ between $t$ and $t + 1$. Where $A$ is the Makeham term, which is an age-independent risk of death per year (such as an accident); The exponential term, $\frac{B}{C} \cdot (e^{C \cdot (a_{i,t} + \Delta t)} - e^{C \cdot a_{i,t}})$ showing exponential dependence on $a_{i,t}$; The discrete forward difference computes the discrete change over a unit interval $\Delta t = 1$ in an exponential growth/decay process. We then convert the discrete G-M hazard function to a discrete probability $\pi(a_{i,t})$ to compute the probability of survival in each $t$.

$$\pi_{\text{death}}(a_{i,t}) = 1 - e^{-\mu(a_{i,t})} \quad \text{with capped} \quad 0 \leq \pi_{\text{death}}(a_{i,t}) \geq 1 \tag{4}$$

However, death does not occur homogeneously to all individuals of the same age $(a_{i,t})$, as is supposed in representative agent frameworks. We introduced a realistic death pattern in which individuals of the same age die at different periods, determined by a stochastic process, such that an individual $i$'s death or survival at $t$ is determined, if an individual $i$ is alive at $t-1$, then

$$a_{i,t} = \begin{cases} a_{i,t-1} + 1 & \text{if} \quad U(0,1) > \pi_{\text{death}}(a_{i,t-1}) \\ \text{NA} & \text{if} \quad \text{Otherwise} \end{cases} \tag{5}$$

Thus, this implies that an individual's survival and ageing process also depends on stochastic components taken from a uniform distribution $U(0,1)$, and if the uniform probability is greater than the death probability computed in equation 4, an individual survives the next period and the age increases by $+1$, while if the uniform probability is less than or equal to the death probability, the individual dies and cannot give birth to offspring (we update the corresponding row at the time of death with $NA$).

This implementation aligns with the standard cohort-component demographic models (Booth, 2006; Yusuf, Martins, & Swanson, 2014), but it provides a realistic period-by-period mortality. The stochastic survival mechanism means that even at older ages, some individuals can outlive those at younger ages, though this is less likely. This allows us to capture individual heterogeneity in longevity, which is crucial in intergenerational transmission, since it determines when heirs will received inheritances-often assumes to be constant at older ages in most existing studies, such as those of (Zagheni & Wagner, 2015).

**Age-Specific Fertility Rate (ASFR)**

As individuals survive and age over time, they can give birth to offspring who also survive and age with the same mechanisms of the parent ageing and survival process in equation 4. However, to prevent an unrealistic scenario in which every individual gives birth, we defined an age range for giving birth of $15-49$ years. Such that, if an individual has an age $a_{i,t} \in [15-49]$, and has a fertility probability greater than a uniformly drawn fertility, the individual gives birth to offspring. We incorporate the cohort age-specific fertility schedule recorded in empirical data, which defines fertility rates across age groups (Osterman, Hamilton, Martin, Driscoll, & Valenzuela, 2025). This standard cohort fertility schedule represents fertility across cohorts of women per thousand in a specific period. Therefore, we converted the standard births per

$1000s$ women to births per woman as

$$r(a_{i,t}) = \frac{ASFR(a)}{1000} \tag{6}$$

Where the $ASFR(a)$ is the reported age-specific fertility births per $1000s$ of women for each age cohort, and the denominator allows us to compute births per woman. Thus, since the rate $r(a_{i,t})$ gives an annual birth rate for each individual, we then transform these rates to birth probability.

$$p_{fert}(a_{i,t}) = 1 - e^{-r(a_{i,t})} \quad \text{with capped} \quad 0 \leq p_{fert}(a_{i,t}) \geq 1 \tag{7}$$

This transformation provides an individual-level birth rate for each woman's birth decision at time $t$ by transforming the population cohort-level statistics.

**Birth Event**

Similarly, to prevent all agents within the fertility age range from giving birth, we provide a realistic scenario in which fertility follows a stochastic process—in this case, an individual can be within the fertility age range, but the probability drawn from a uniform distribution determines if the individual gives birth to offspring, which holds for all individuals in all generations. Thus, at time $t$, if an individual $i$ is alive (i.e. $a_{i,t} \neq NA$) and age $a_{i,t} \in [15, 49]$, a uniform draw $U(0, 1)$ will determine if a new generation individual is born, and this birth process is represented as;

$$a_{j,t}^{child} = \begin{cases} 1 & \text{if} \quad p_{fert}(a_{i,t})^{mother} > U(0,1) \quad \text{and} \quad a_{i,t} \in [15, 49] \\ 0 & \text{if} \quad \text{Otherwise} \end{cases} \tag{8}$$

Where $a_{j,t}$ is the age of a newborn individual, either in the first, second or third generation. Every time a birth occurs in any generation, the corresponding row matrix of that generation's children and at that corresponding time $t$, represented by the column, is updated. Each newborn child is dynamically appended to her generational matrix, which implies that each row in the matrix indicates the sequence of births that first occur.

Additionally, the age of each new child born $a_{j,t}^{child}$ is updated and increased in the next period, $t + 1$, given by the same condition of the parent age progression in equation 5, and the age of the newborn child increases by

$$a_{j,t}^{child} = \begin{cases} a_{j,t-1}^{child} + 1 & \text{if} \quad U(0,1) > \pi_{death}(a_{j,t-1}) \\ NA & \text{if} \quad \text{Otherwise} \end{cases} \tag{9}$$

Moreover, we assign a heterogeneous random birth spacing[2] for each individual taken from

[2]For simplicity, at the current formulation, the heterogeneous birth spacing is given at random from a sample, thus it's not affected by individual wealth or human capital. Future extension could be in this direction to allow for a feedback mechanism between the demographic and the economic sector. For instance, we can allow an individual's level of education or wealth to affect their fertility choice by opting for longer birth spacing. This is a crucial determi-

random sample $s_i \sim \mathrm{U}(3, 4, 5)$ and after every individual birth, $t - \tau_i \geq s_i$ the last period in which an individual gives birth is updated to prevent frequent births which is given as; $\tau_i \leftarrow t$; where $t$ is the current time, $\tau_i$ is the time of the recent birth of each individual and the term $t - \tau_i \geq s_i$ make sure that each new birth satisfies the individual birth spacing at time $t$. This also ensures that there is heterogeneity in fertility both across and within cohorts and matches the empirical and biological fertility pattern with realistic intervals.

This heterogeneous demographic simulation allows multi-generations to coexist, and allows detailed tracking of individuals of the same lineage (see figure 1 family tracking), which is crucial to examining how family resources influence child human capital accumulation and how the transfer of wealth drives inequality across generations. In addition, with this framework, we can examine how demographic factors affect intergenerational transmission by changing the parameters of the G-M function, fertility schedule or incorporating feedback between economic and demographic variables.

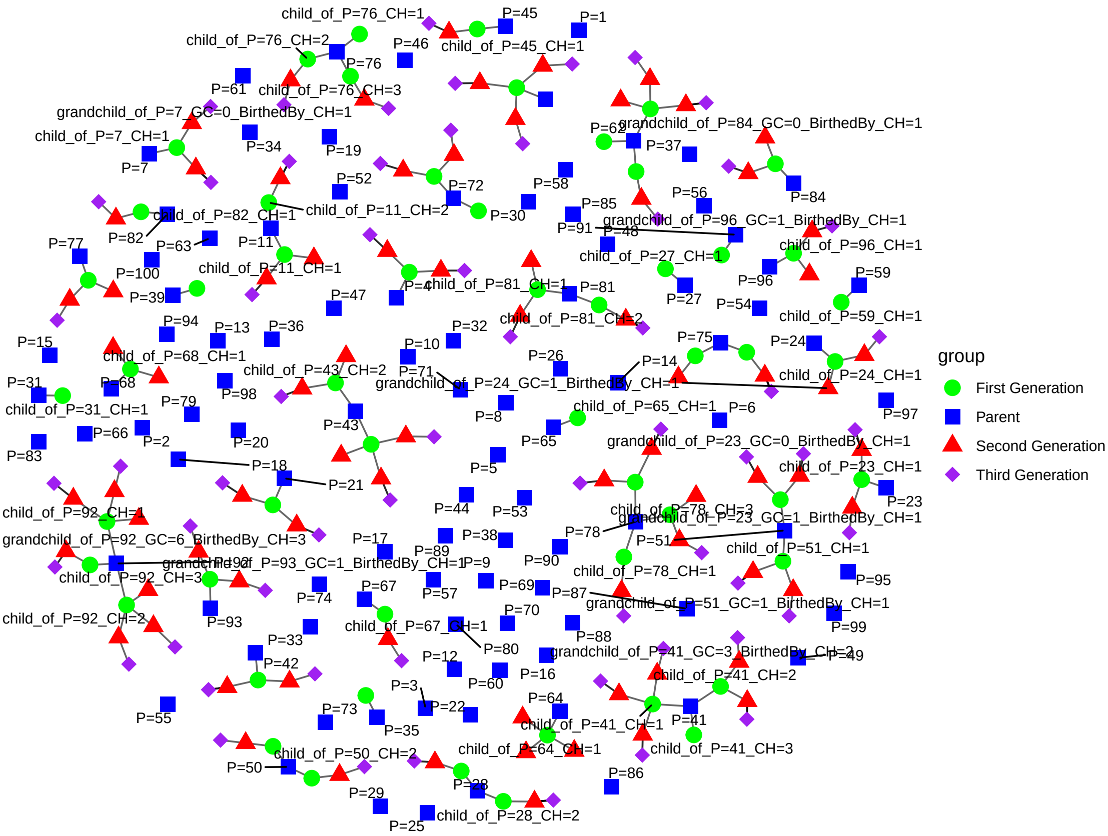



Figure 1: Family Tree

nant for the quantity-quality trade-off and leading to the demographic transition observed in advanced economies (Galor, 2011)

## 3.2 Economic Life-Cycle

### Human Capital Formation

The demographic behaviours are dynamically integrated with the economic behaviours such that at each time $t$, individuals $i$ will make both demographic and economic decisions. As individuals age, they accumulate human capital through schooling. We simulate year-by-year educational progress from early childhood to young adulthood. Each time $t$, a child may advance (gain another year of schooling) with a probability that depends on the parent's wealth[3] and the number of siblings in the household, which dilutes parental wealth.

Let $h_{i,t}$ denote the years of schooling (human capital) of individual $i$ at time $t$, and $a_{i,t}$ be the age of individual $i$ at time $t$. The parent of individual $i$ has wealth $w^p_{i,t}$. The number of school-age siblings (including the individual) is denoted by $s_{i,t}$ (count of siblings aged $6-24$). We define the effective wealth as:

$$\tilde{w}^p_{i,t} = \frac{w^p_{i,t}}{\sqrt{1+s_{i,t}}} \tag{10}$$

The $\tilde{w}^p_{i,t}$ term implies that there is resource dilution within the household, such that if a household has more than one child of school-age, it will have a diminishing effect on parental resources, thus reducing the probability of educational attainment. This is crucial for the quantity-quality trade-off (Becker, 1992; Becker & Tomes, 1986; Galor, 2011), and allow use to examine the effect of household size on educational outcome, ensuring that given households of the same parental wealth, the children in the households with fewer young children will have a higher probability of attaining additional years of schooling. The probability of obtaining an additional year of education is given as:

$$\text{logit}_{i,t} = \begin{cases} \ln\left(\dfrac{p_h}{1-p_h}\right) + \beta^h_W\, z_{i,t} & \text{if } 6 \le a_{i,t} \le 18 \text{ and } h_{i,t-1} < 12, \\ \ln\left(\dfrac{p_{ph}}{1-p_{ph}}\right) + \beta^{ph}_W\, z_{i,t} & \text{if } 19 \le a_{i,t} \le 24 \text{ and } 12 \le h_{i,t-1} < \min(18, a_{i,t}-6), \end{cases} \tag{11}$$

where $\beta^h_W$ and $\beta^{ph}_w$ capture the wealth sensitivity in the two stages and $z_{i,t}$ is the normalised (see Appendix 53) parental wealth effect on educational progression, relative to the median household's wealth.

The linear index is then mapped to a progression probability via the logistic link:

$$\kappa_{i,t} = \frac{1}{1+e^{-\text{logit}_{i,t}}}, \qquad \kappa_{i,t} \in [0.01,\, 0.99] \tag{12}$$

where we cap probabilities to avoid degenerate $0/1$ outcomes in finite samples. Therefore, an individual's human capital then follows a stochastic accumulation rule applied annually over

[3] At the current form, parental education does not affect children's education, a factor which has been well-documented in many human capital accumulation theories (Cunha & Heckman, 2007). Further extension can include this factor to enhance realism

schooling ages:

$$h_{i,t} = h_{i,t-1} + \Delta h_{i,t}, \qquad \Delta h_{i,t} \sim \text{Bernoulli}(\kappa_{i,t}). \tag{13}$$

This stochastic process of accumulation will generate an instance; despite children from wealth households having a higher probability of attaining more schooling years, there is also a possibility that they can have a lower level of education. Together, these formulations are empirically grounded and reflect findings that family resources have little effect on early schooling progression due to the public and compulsory education, while the transition beyond high school is more sensitive to credit constraints and family wealth (Belley & Lochner, 2007; Cameron & Heckman, 2001; Carneiro & Heckman, 2002; Lochner & Monge-Naranjo, 2012). Thus, this allows, at the bare minimum child from a less advantaged parent to attain some level of schooling, while progressing to a higher level, will significantly depend on parental wealth.

Most importantly, in our intergenerational transmission case, as children complete schooling, they enter adulthood with a level of human capital $h_{i,t}$ (years of schooling)[4]. This is a crucial novelty of our approach, which endogenously produces human capital distribution across generations, rather than imposing it exogenously, which aligns with the demonstration of (Cagetti & De Nardi, 2008) that modelling human capital endogenously will generate the observed data on earnings. This is because the differences in family resources can lead to educational inequality, which will translate to earning inequality (Benhabib & Bisin, 2018; Galor & Zeira, 1993), and how inheritance taxation can serve as a tool for both redistribution and predistribution, demonstrated by (Cowell et al., 2018).

**Productivity**

Each $i$ at time $t$, enters the labour market with human capital $h_{i,t}$, which affects their productivity. As a classical Mincer-style formulation, here human capital does not affect earnings directly; it rather enhances productivity, which translates to higher earnings in the labour market. The productivity function is given by:

$$\ln p_{i,t} = \beta_0 + \beta_1 h_{i,t-1} + \beta_2 exp_{i,t} + \beta_3 exp_{i,t}^2 \tag{14}$$

where $\beta_0$ is the base productivity level, such that individuals with zero human capital are assigned this baseline productivity; $\beta_1$ is the return to past accumulated human capital; $\beta_2$ is the effect of experience, such as job-market experience, which raises individual productivity. However, an individual's experiences diminish over the life cycle, capturing the learning that eventually plateaus, which is captured by the quadratic (concavity) of $\beta_3 < 0$[5]. An individual

[4]It is important to note that, the parent generation human capital is taken as a stock, which is determined at birth, during the initialisation process at $t = 1$. See initialisation process in Appendix B.1

[5]Other studies examine the concavity of human capital due to depreciation of human capital as an individual ages, or declines in cognitive declines (Angrisani & Lee, 2019; Hanushek, Kinne, Witthöft, & Woessmann, 2025; Kimura, Kurachi, & Sugo, 2022). However, recent studies also pointed out that cognitive training exercises can mitigate this declining effect, so we do not include a declining human capital term.

experience is measured by $exp_{i,t} = \max(0, a_{i,t} - a_0)$, implying an individual starts to accumulate experience form the age at which an individual enters the labour market $(a_0)$[6].

Moreover, the $\beta_0$ is calibrated such that the median productivity is normalised $p_{i,t}$ to 1. We set

$$\beta_0 \;=\; -\,\text{median}\big(\beta_1 h_{h,1} + \beta_2 \text{exp}_{h,1} + \beta_3 \text{exp}_{h,1}^2\big) \tag{15}$$

where $h_{h,1}$ and $exp_{h,1}$ are computed from the initial distribution of human capital and experience[7]. This ensures that the median, $\ln(p_{i,t}) = 0$ and hence the median in levels $p_{i,t} = 1$. This normalised the median productivity in equation 16 to 1 makes the calibrated base wage $w_0$ (in equation 17) equal to the empirical median wage (an individual with $p_{i,t} = 1$ therefore earns $w_0$), while avoiding distortions from skewed productivity components that would affect a mean-based centering.

Moreover, since the productivity function is in natural logs, we exponentiate to compute productivity in levels and always greater than zero.

$$p_{i,t} = \begin{cases} e^{\ln p_{i,t}} & \text{if} \quad a_0 \le a_{i,t} \le a^r \\ 0 & \text{if} \quad \text{otherwise} \end{cases} \tag{16}$$

where $a^r$ is the retirement age, implying individuals not in the working age have zero productivity and earnings. In a nutshell, this formulation of the productivity function ensures that we can capture the empirical life cycle U-shape pattern of individual productivity, which increases with age and then declines after reaching a peak age.

**Labour Income**

Given each $p_{i,t}$, each $i$ earns labour income at $t$, differentiated by human capital and experience, to capture the heterogeneity in returns.

$$y_{i,t}^{\text{lab}} = w_0 \, p_{i,t} \, e^{\xi_{i,t}} \tag{17}$$

where $w_0$ is the base earnings, which is the estimated annual median earnings of households and scales the level of wages[8].

$$\xi_{i,t} \sim N(\mu_\xi, \sigma_\xi^2) \tag{18}$$

$$\mu_\xi = -\tfrac{1}{2}\sigma_\xi^2 \quad \text{and} \quad \mathbb{E}[e^{\xi_{i,t}}] = 1 \tag{19}$$

[6]This also implies that children can simultaneously work and school, as long as they reach the labour market entry age. This could be enhanced in future work such that individuals obtaining schooling can enter after completion, while those who could not due to, for instance, lack of family resources, work when they reach the entry age

[7]Measure by the difference between the initialised parent ages and $a_0$ (see the initialisation of the age samples and years of schooling of the parent at $t = 1$ in equation B.1

[8]When $p_{i,t} = 1$, labour income equals the calibrated median wage $w_0$. Without the mean-correction, the log-normal shock would raise average earnings above this benchmark.

The transitory idiosyncratic shock $\xi_{i,t}$ is i.i.d. across individuals and periods. We set the mean of the shock to (the mean-correction) ensure that the exponent of the shock have unit expectation, so that random fluctuations are pure transitory risk without affecting the long-run average earnings, and thus $\mathbb{E}[y_{i,t}^{lab}] = w_0 \cdot p_{i,t}$. The incorporation of transitory shock generate realistic heterogeneities within individuals of the same human capital and experience. While its mean correction ensures the shock introduces dispersion without changing the expected level of labour income conditional on $p_{i,t}$. This approach is standard in macroeconomics literature to maintain consistency with empirical earnings moments while allowing realistic volatility. Our earning function follows a simplified representation of income processes, wealth–accumulation literature, which often includes both permanent and transitory components (Cagetti, 2003; Carroll, Slacalek, Tokuoka, & White, 2017). However, this formulation will allow us to generate how individual differences in earnings are due to heterogeneity in human capital as a result of family advantage, which leads to different accumulations.

This earning function will follow the hump-shaped earning profiles documented in life cycle literature (Agénor, 2004; Attanasio & Weber, 1993; Fernández-Villaverde & Krueger, 2007), due to the hump in $p_{i,t}$ (which rises with experience and then declines mid-career). Therefore, with this formulation, individuals with different levels of human capital will end up with different earnings capacity, due to productivity; thus, inequality in educational attainment between children from wealthier or poorer families will end up at different positions in the income distribution. However, the shock component implies that even children from the same wealthy households can end up with different earnings.

#### Financial Income and Returns on Wealth

An individual earns financial income from their past accumulated wealth, which supplements labour income and helps smooth consumption when labour income is low or absent (e.g., during retirement), in the tradition of the buffer stock framework. Their financial income at each $t$ is given by:

$$y_{i,t}^{\text{fin}} = r_{i,t} \cdot w_{i,t-1} \tag{20}$$

where $w_{i,t-1}$ represents wealth from the previous period and $r_{i,t}$ is the rate of return on previous wealth, which follows:

$$r_{i,t} = \bar{r} + \underbrace{\phi \ln(1 + \frac{w_{i,t-1}}{W_{50}})}_{\text{wealth premium}} + \epsilon_{i.t}^{r} \tag{21}$$

$$\text{where} \quad r^{min} \leq r_{i,t} \leq r^{max} \quad \text{and} \quad 0 \leq \phi \ln(1 + \frac{w_{i,t-1}}{W_{50}}) \leq w^{p}$$

The return on past accumulated wealth is composed of a fixed wealth independent return $\bar{r}$. This parameter $\bar{r}$ represents the baseline or expected annual rate of return on wealth, a wealth-dependent return (wealth premium), and a wealth-dependent stochastic component $\epsilon_{i.t}^{r}$. The wealth premium is capped between $[0, w^p]$ for numerical stability. The term $w^p$ is the maximum possible value of the wealth premium.

The stochastic component of the return also comprises a wealth-dependent volatility and a random shock, which are given as:

$$\epsilon^r_{i,t} = \sigma(w_{i,t})^{vol} \cdot \eta_{i,t} \quad \text{with} \quad \eta^r_{i.t} \sim t_{\eta_{i,t}} \tag{22}$$

$$\sigma(w_{i,t})^{vol} = \begin{cases} \sigma^{vol}_{\min} + (\sigma^{vol}_{\max} - \sigma^{vol}_{\min}) \cdot [(1 - e^{-\psi \ln(1+\frac{w_{i,t-1}}{W_{50}})})] & \text{if} \quad w_{i,t-1} > 0 \\ \sigma^{vol}_{\min} & \text{if} \quad w_{i,t-1} \leq 0 \end{cases} \tag{23}$$

$$\text{where} \quad \sigma^{vol}_{min} \leq \sigma(w_{i,t})^{vol} \leq \sigma^{vol}_{\max}$$

This implementation implies that wealthy individuals take more investment risk, which aligns with empirical evidence that richer households have better access to sophisticated financial instruments and can thus afford to take larger risks due to greater buffer wealth (Benhabib, Bisin, & Zhu, 2011; Cagetti & De Nardi, 2006; Fagereng, Guiso, Malacrino, & Pistaferri, 2020; Quadrini, 2000). In addition, the wealthier the individual, the higher the volatility, but with a decreasing rate, which creates a "Matthew effect", indicating early wealth advantage will lead to better opportunities, which will lead to a large future advantage, thereby making inequality persistent and path-dependent. For individuals with no wealth, they received the minimum volatility, $\sigma^{vol}_{min}$, which ensures households with no net wealth will have (such as interest-rate risk on deposits), creating uncertainty and preventing inequality bias. Furthermore, the volatility is scaled (see scaling in equation 69 in Appendix) with the t-distribution to have a unit variance, such that the shock is equivalent to the volatility and volatility is directly interpretable as the standard deviation of the return shock. Moreover, to prevent an unrealistic and numerical instability, we capped the wealth volatility and the total expected return on wealth to empirically possible values. The latter is capped to a maximum and minimum value to allow loss and gain in total returns (in equation 21), while the former is capped between the minimum and maximum volatility (in equation 23).

Put together, this formulation models the rate of return on wealth as heterogeneous and increasing in wealth, which is empirically grounded in literature showing that wealthier investors often achieve higher returns due to better financial advice, risk-taking, and other factors (Benhabib & Bisin, 2018; Fagereng et al., 2020; Piketty & Saez, 2014). However, the individual wealth premium and volatility are relative to the household's median wealth ($W_{50}$), such that if the median wealth increases, the wealth premium will fall, while the log functional form ensures that individual return increases with wealth but exhibits diminishing returns as individuals accumulate more wealth. Furthermore, the return on past wealth varies across time and the t-distribution introduces uncertainties in return on past wealth, and allows us to model heavy tails in returns to capture periods with large positive or negative shocks (Cont, 2001) that reflect occasional big gains or losses in assets return, which is key to understanding the distribution of wealth documented by Benhabib and Bisin (2018), and this Stochastic and explosive returns on wealth have been identified as a key factor driving wealth concentration that is more skewed than earnings.

### Disposable Income

An individual's $i$ disposable income at $t$ also comprises the transfers received from government redistribution. The disposable income is represented as:

$$y_{i,t}^{d} = \begin{cases} y_{i,t}^{lab} + y_{i,t}^{fin} + T_{i,t-1} & \text{if} \quad \text{Receive transfer} \\ y_{i,t}^{lab} + y_{i,t}^{fin} & \text{if} \quad \text{Otherwise} \end{cases} \tag{24}$$

Where $T_{i,t-1}$ is the government transfers an individual receives from the previous period as part of the social benefit. In this framework, government transfers will help us examine the effect of redistributional policies as a form of predistribution (Cowell et al., 2018) in acting as a level playing field to create an initial advantage for poorer households, which will then be used to enhance human capital development (Galor & Zeira, 1993) of their children, boosting earnings and the wealth accumulation process, which is a key mechanism of mitigating intergenerational inequality.

### Equivalent Income

Studies often compare households' well-being using the equivalent income, which accounts for the household size and composition on per capita consumption (Clementi & Gallegati, 2005; Nolan, Richiardi, & Valenzuela, 2019). This household adjustment creates a channel through which demographic variables, such as fertility, will affect a household's consumption levels, such that households composed of many individuals will have a lower per capita income available for consumption. We used the modified OECD equivalent scale measures, which assign different consumption weights between children and adults; this implies that adult individuals in a household have more consumption needs than children. The modified OECD scale is given as:

$$\varnothing_{i,t} = 1 + 0.5\,(n_a - 1) + 0.3\,n_c \tag{25}$$

where $\varnothing_{i,t}$ is the total number of individuals in a household; $n_a$ is the presence of an extra adult individual in a household, and $n_c$ is each young child present in a household. This transforms household equivalence income to compare the consumption across households.

$$y_{i,t}^{eq} = \frac{y_{i,t}^{\mathrm{d}}}{\varnothing_{i,t}} \tag{26}$$

In our framework, an adult member in a household is the head of the household (i.e. mother), and each child of this household head who is at least $14$ years of age, but still in the schooling age (i.e. $14 \leq a_{i,t} \geq 24$) is counted as an adult, while all other children that are $a_{i,t} < 14$ are counted as children and thus, they have lower consumption weight of 0.3, compare to the consumption weight of 0.5 for those whose ages are greater and the household head have a consumption weight of 1. This implies that immediately, a child completes post-high school, they are not included in the consumption decision of their mothers. However, they still receive inheritances upon the death of the mother or family member(s).

**Consumption and Savings**

Individual and household consumption patterns play a crucial role in the wealth accumulation process. This pattern determines how much is saved to accumulate wealth, which is influenced by household size and composition. Households consume from their past accumulated wealth and disposable income given by:

$$c_{i,t} = \text{mpy}_{i,t} \cdot y_{i,t}^{dis} + \text{mpw}_{i,t} \cdot w_{i,t-1} \tag{27}$$

Where $y_{i,t}^{dis}$ is the disposable income of individual $i$ at the time $t$; $w_{i,t-1}$ is the stock of wealth of the individual accumulated from $t-1$. Studies on consumption profile, commonly documented in the life cycle framework, often report hump-shaped consumption due to consumption smoothing, as individuals smooth consumption across different periods of their life cycle, due to the certainty equivalent assumption (Agénor, 2004; Attanasio & Weber, 1993). Without assuming households' smooth consumption at different stages of their life cycle, as Fernández-Villaverde and Krueger (2007) demonstrated, allowing demographic factors to affect households' preferences will produce this hump-shaped consumption pattern.

Given that in this framework, household size and composition affect household income, this affects households' marginal propensities to consume, such that the larger the number of individuals in a household, the larger the household's consumption needs, thus increasing their marginal propensity to consume on the disposable income. Therefore, we formulate the household's marginal propensity out of income and wealth using the functional form:

$$\text{mpy}_{i,t} = \begin{cases} \frac{\bar{c}_y}{1+\alpha_y \cdot (y_{i,t}^{eq})^{\gamma_y}} & \text{if} \quad y_{i,t}^{eq} > 0 \\ 0 & \text{if} \quad a_{i,t} < a_0 \end{cases} \tag{28}$$

$$\text{mpw}_{i,t} = \begin{cases} \frac{\bar{c}_w}{1+\alpha_w \, w_{i,t-1}^{\gamma_w}} & \text{if} \quad w_{i,t-1} > 0 \\ 0 & \text{if} \quad a_{i,t} < a_0 \end{cases} \tag{29}$$

where $\text{mpy}_{i,t}$ and $\text{mpw}_{i,t-1}$ are the marginal propensities to consume out of income and past wealth, $\gamma_y$ and $\gamma_w$ are the elasticity of marginal propensities to consume with respect to income and wealth, while $\alpha_y$ and $\alpha_w$ capture how the marginal propensities decline with income and wealth, respectively. The functional forms of these marginal propensities imply that children not in the labour force ($a_{i,t} < a_0$) do not consume their wealth, in case they received inheritances earlier, and thus their consumption is handled by their mothers, which thereby prevents them from de-cumulating their inheritances early. Thus, the marginal propensities are bounded such that $0 \leq \text{mpy}_{i,t} \leq \bar{c_y}$ and $0 \leq \text{mpw}_{i,t} \leq \bar{c_w}$ to anchor the marginal propensities to their maximum and to the empirically values.

Many representative agent models assumed homogeneous marginal propensities to consume across households, which has not been the case in the empirical data. Carroll et al. (2017); Garbinti, Lamarche, Savignac, et al. (2022); Kaplan and Violante (2014) reported heterogeneities in marginal propensities and wealth distribution across the distribution. The wealthy have lower marginal propensities than the poor, and they save more (**?**). These functional forms capture these empirical facts on household consumption behaviours across the distribution.

Moreover, the residual of consumption, i.e. the part of their disposable income that is not consumed, is saved to accumulate more wealth over time, given by:

$$s_{i,t} = y_{i,t}^{\text{dis}} - c_{i,t} \tag{30}$$

The motive for saving plays a crucial role in the wealth accumulation process, and households will respond differently to policy based on their motives for saving. As we mentioned earlier, we can relax some of the assumptions on households by properly calibrating the marginal propensities in equation 29 and equation 28, to allow households to behave like hand-to-mouth consumers or model a bequests economy, in which parents prefer to leave transfers to their heirs, which can be achieved by lowering $\bar{c_w}$ and $\bar{c_y}$ to allow households to save aggressively.

**Wealth**

As demonstrated in Benhabib and Bisin (2018), wealth accumulation is a result of individual consumption and savings behaviours in addition to the skewed distribution of earnings. The savings rate enables individuals to accumulate wealth over time. The larger the savings of households, the more households will amass wealth and invest in riskier assets such as stocks and bonds (Fagereng et al., 2020), which generate higher rate returns and lead to exponential growth in wealth. However, even if individuals have the same savings rate, the heterogeneities in returns can lead to different wealth ownership. An individual's wealth accumulation is given by:

$$w_{i,t} = \begin{cases} w_{i,t-1} + s_{i,t} + Ih_{i,t-1} & \text{if} \quad \text{received} \quad \text{inheritance} \\ w_{i,t-1} + s_{i,t} & \text{if} \quad \text{no inheritance} \end{cases} \tag{31}$$

Where $w_{i,t-1}$ is the past wealth accumulated wealth, $s_{i,t}$ is the current savings, while $Ih_{i,t-1}$ is the amount of inheritance a heirs received from a testator from the previous period, which allows us to examine the effect of inheritances on the distribution of wealth.

This implies that households with different savings can end up with different levels of wealth, which can be bequeathed intra- or intergenerationally, affecting the concentration of wealth. The effect of demographic variables such as family size, composition and the length of life of the testator affects the effect of inheritance in perpetuating the level of inequality. In this formulation, if a testator, such as a parent, dies earlier, this will allow the heirs to receive wealth at a young age, before entering the labour market, which will enable them to save and earn returns to accumulate wealth earlier. Specifically, family size affects the amount of inheritance individuals will receive after the death of the testator; the heirs of a testator with lower wealth but a smaller family size can start with higher initial wealth than a richer household with a larger family size, thus, the heterogeneities in family size can have different effects on wealth inequality regardless of the wealth of the testator at death.

### 3.3 Inheritance

To examine the full effect of inheritance, we incorporated a sophisticated inheritance transfer mechanism, as shown in figure **??**, moving away from simple parent-child transfer–which is a key strength of this framework. This wealth transfer process includes an inheritance flow mechanism that is lineage-based and hierarchical to ensure that wealth is passed to the closest living relatives according to a fixed priority order. This sophisticated wealth transfer mechanism is evidenced in (Gale & Scholz, 1994), who documented the percentage of intergenerational direction of wealth transfer from $1983 - 85$.

When an individual dies at $t$, their accumulated wealth at $t-1$ is distributed according to the inheritance flow mechanism, which does not allow for any disappearance of wealth when an individual dies. However, before the accumulated wealth of a deceased individual in any generation is transferred to their eligible heir as inheritance, the wealth is taxed before it is added to the wealth of the heir(s). The inheritance tax process and the distribution of the inheritance to the beneficiary are represented as.

$$IR_{i,t} = \iota_{rate} \cdot w_{i,t-1}^{deceased} \tag{32}$$

$$Ih_{i,t} = w_{i,t-1}^{deceased} - IR_{i,t} \tag{33}$$

where $\iota_k$ is the inheritance tax rate, thus changing this tax rate, we can observe how varying tax rate affects transfers; $w_{i,t-1}^{deceased}$ is the the total wealth of the deceased individual in the previous period[9], which is available to be inherited by heir, after deducting taxes, $IR_{i,t}$ at each time $t$. Furthermore, the inheritance taxes collected in each $t$ become revenue for the government, thus at the end of each period $t$, the government sums all taxes collected and adds it to its revenues in equation 35, which is then used for redistribution in the economy.

However, if a deceased individual $i$ at the time of death $t-1$ does not have any surviving family member, the wealth of this individual is added to the endowment fund at time $t$, which also becomes a revenue for the government. Thus, after every period $t$ government also adds

[9]This is implemented, after searching for a deceased individual$i$ at time $t$, we collect the accumulated wealth of this individual in the previous period $t-1$, to be distributed after tax.

all the unclaimed wealth to its revenue to distribute it back in the economy.

$$F_t = F_{t-1} + \sum_{\text{unclaimed}}^{T} w_{\text{unclaimed},t-1} \tag{34}$$

### 3.4 Government

At the end of each period $t$, the government earns revenues from inheritance taxation $IR_t$ and the pooling of the unclaimed wealth $F_t$, given by:

$$R_t = \sum_{t=1}^{T} IR_{i,t} + \sum_{t=1}^{T} F_{i,t} \tag{35}$$

In this framework, the government imposes tax policies on all inheritances before they are passed on to beneficiaries, which is a source of revenue for redistribution policies that might help reduce inequality. In addition, the unclaimed wealth, due to no available heirs, upon the death of an individual from all generations, is also revenue available for the government for redistribution in the economy. Thus, at the end of each period, government revenues received from taxes on inheritance and unclaimed wealth are given as;

#### 3.4.1 Redistribution

**Equal Benefits: All surviving Individuals**

The government revenues are redistributed back to the economy in the form of social benefits to individuals, which helps us to examine the scenario in which government redistributions go to all surviving individuals, regardless of the wealth, income or age of the individuals, given by:

$$N_{\text{surviving},t} = \sum_{t=1}^{T} a_{i,t} \neq \text{NA} \tag{36}$$

$$\text{Benefit}_{i,t} = \frac{R_t}{N_{\text{surviving},t}}, \quad \forall i \in N_{\text{surviving},t} \tag{37}$$

However, this is just a baseline. More robust and realistic redistributional policies can be implemented in future work. For instance, instead of equal redistribution to all, the government can engage in means-tested redistribution, in which benefits are paid to poorer individuals, poor retirees, or individuals in the working population, since the consumption of children is handled by their parents.

### 3.5 Simulation Design

At each $t$ of the simulation, we stored all demographic and economic information of all generations. When a new child is born, we dynamically append their row index to the row of their specific generational matrices of each demographic and economic variable. The rest of the simulation design follows the following sequences:

1. ***Initialisation:*** At $t = 1$, from the disaggregation of the initial households into cohorts with proportions of each cohort, we generated an initial distribution of wealth and human capital (see appendix B.1), which is assigned to these individuals. However, human capital is fixed for this generation, while wealth accumulates through the accumulation process in equation 31

2. ***Iterative Simulation Loop:*** At the start at $t = 2$, thus, for each $t$ simulation search for each $i$ that survives in $t - 1$. If an individual survived, their age is $a_{i,t} = a_{i,t-1} + 1$, if an individual dies in $t - 1$, then their age is set to $a_{i,t} = NA$. The survival and death process are given in equation 4.

3. ***Cohorts:*** For all surviving individuals at $t$, the simulation identifies all those that are young, working or retirement age, given by the cohort disaggregation in equation 2.

4. **Economic decision**

   - ***Productivity:*** Given each age cohorts, each individual $i$ productivity $p_{i,t}$ is computed from their age at $t$ and past attained education (i.e. $h_{i,t-1}$).
   - ***Earnings:*** From each $i$ productivity at $t$, we compute their labour income $y_{i,t}^{lab}$ which depends on their $p_{i,t}$ and transitory income $\xi_{i,t}$ shock.
   - ***Return realisation:*** From individuals' past accumulated wealth $w_{i,t-1}$, we compute the expected return $r_{i,t}$ on the past accumulated wealth as given by the expected return formulation in equation 21, which comprise of average annual return, wealth dependent premium and volatility shock.
   - ***Financial Income*** Each individual $i$ financial income $y_{i,t}^{fin}$ is then computed from their expected return $r_{i,t}$ and past accumulated wealth $w_{i,t-1}$.
   - ***Disposable Income:*** An individual $i$ disposable income $y_{i,t}^{dis}$ is computed from the sum of their $y_{i,t}^{fin}$, $y_{i,t}^{lab}$ and transfers $T_{i,t-1}$ received from past redistribution by the government.
   - ***Equivalent Income:*** Before computing an individual equivalent income $y_{i,t}^{eq}$, we search the number of children each $i$ has at $t$, and identify their ages to weight their consumptions. The total household size and composition are then computed using the modified OECD scale demonstrated in equation 25. Finally, from each $y_{i,t}^{dis}$, we factor in the household size and consumption to obtain $y_{i,t}^{eq}$.
   - ***Marginal Propensities to consume:*** We compute $mpy_{i,t}$ from $y_{i,t}^{eq}$ and $a_{i,t}$, as well as $mpw_{i,t}$ from their $w_{i,t-1}$ and $a_{i,t}$
   - ***Consumption and Savings:*** From individual marginal propensities out of income and wealth (i.e. $mpy_{i,t}$ and $mpw_{i,t}$ respectively), we compute their current consumption $c_{i,t}$, from their disposable income and past accumulated wealth. The remaining of their disposable income (i.e. the residual from consumption) is saved at $t$

- ***Wealth Accumulation:*** Each individual $i$ accumulate wealth at $t$ (i.e. $w_{i,t}$) from their current savings $s_{i,t}$ and their past accumulated wealth $w_{i,t-1}$. Additionally, if an individual receives an inheritance at the end of the previous period (i.e. $Ih_{t-1}$), these inheritances are added to the current wealth $w_{i,t}$.

5. ***Demographic decision:*** At the end of each $t$ economic decisions of individuals, we identify all individuals in the childbearing age as mentioned in equation 8, whose fertility probabilities meet the birth condition and their last period of birth satisfies their individual birth spacing. Moreover, after every birth at $t$, we dynamically append newborn children in the row of their generation matrices, assign them IDs, link them to their lineage and count the index of the children among the children of a mother, as well as her index in the grand and great-grandparent. Finally, we assign all new born shocks variables and birth spacings.

6. ***Inheritance:*** At the end of all economic and demographic decisions, we identify deceased individuals in $t$, collect their wealth at death $t$, and identify their eligible heirs who survive at $t$. After identifying the heirs of deceased individuals, the inheritance tax is deducted from the deceased's wealth, and the remainder is transferred to the heir as inheritance. However, for all deceased individuals who do not have children or surviving heirs at death, their wealth is transferred to an endowment fund. In this framework, there is also the possibility of inheritance by ascendant (i.e. reverse bequests), if the decease do not have a surviving child at death.

7. ***Redistribution:*** The government, at the end of the economic, demographic and inheritance process at each $t$, collects all taxes received from inheritance and unclaimed wealth in the endowment fund and redistributes all these revenues to all surviving individuals.

8. ***Output and Tracking:*** Finally, at the end of each period $t$, we compute aggregates of each variable and inequality metrics (such as Gini Coefficient, Percentile shares). The final result of the simulation is obtained by taking the median values of each variable at $t$ across all the Monte Carlo simulations, which are use for analysis on the effect of inheritance taxation and redistribution on intergenerational inequality.

# 4 Calibration

The AB-OLG model is calibrated to match key empirical moments, including the median household wealth, the wealth Gini, and the distribution of marginal propensities to consume across the income and wealth distribution. Parameters with strong empirical grounding are taken directly from the literature (see Table 1). The remaining parameters, particularly the mortality, marginal propensities to consume and expected returns on wealth, are calibrated through a structural moment-based procedure. We briefly discuss this process here; additional technical details are provided in the appendix.

## 4.1 Demography

The demographic parameters are empirically calibrated using the U.S. life table for $2019$, chosen specifically because this period predates the COVID-$19$ pandemic, which produced spikes in both mortality and fertility that would distort the baseline demographic pattern. High mortality probabilities can affect the timing of inheritance and per Capita redistribution.

### Mortality

The Gompertz slope parameter $C$ is fixed using the mortality doubling time (i.e. $D = \frac{\ln 2}{C}$), which is approximately every $8$ years for the U.S. adult population (Gavrilov & Gavrilova, 2024), a stable feature across low-mortality countries. Thus, from the doubling time, we obtained the value of the G-M slope by:

$$C = \frac{\ln 2}{D} \tag{38}$$

The remaining Gompertz-Makeham parameters $A$ and $B$ are then calibrated by anchoring to two age windows from the U.S. CDC life table (Arias & Xu, 2022), using the average integrated hazard across each window to reduce sampling noise and improve parameter stability. Full derivation of $A$ and $B$ from the discrete G-M function is provided in the appendix C.1.

### Fertility

Additionally, the fertility schedule is also calibrated to the U.S. cohort age-specific fertility rates from the CDC for $2019$ (Osterman et al., 2025). Since the raw estimates are reported as births per $1,000$ women rather than individual probabilities, we first convert them to births per woman (see equation 6) and then apply a Poisson transformation (see equation 7) to obtain individual-level birth probabilities at each period $t$, ensuring internal consistency with the mortality block. The full fertility schedule is provided in the appendix 6. We also provide a visual illustration of how the obtained demographics fit the empirical data, as shown in figure 15

## 4.2 Consumption and Marginal Propensities to Consume

The consumption parameters are calibrated through a structural moment-based grid search procedure, designed to match key empirical targets from the Survey of Consumer Finance (Bhutta et al., 2020). Specifically, we target the heterogeneity in marginal propensities to consume (MPC) across the income and wealth distribution, consistent with evidence that poorer households consume a significantly larger fraction of their income and wealth than wealthier households (Carroll et al., 2017; Dynan et al., 2004; Kaplan & Violante, 2014).

#### Marginal Propensity to Consume out of Income

The MPC out of income mpy is governed by the functional form:

$$\text{mpy} = \frac{\bar{c}_y}{1 + \alpha_y \cdot (y)^{\gamma_y}} \tag{39}$$

where $\bar{c}_y$ is the maximum MPC out of income, anchored to empirical estimates (Jappelli & Pistaferri, 2014; Parker, Souleles, Johnson, & McClelland, 2013), and $\alpha_y$ and $\gamma_y$ govern the rate and curvature at which the MPC declines with income. Similarly, the MPC out of wealth mpw follows:

$$\text{mpw} = \frac{\bar{c}_w}{1 + \alpha_w \cdot w^{\gamma_w}} \tag{40}$$

where $\bar{c}_w$ is the maximum MPC out of wealth, taken from (Carroll, Otsuka, & Slacalek, 2011).

#### Grid Search Procedure

The parameters $(\alpha_y, \alpha_w, \gamma_y, \gamma_w)$ are calibrated jointly by minimising the average calibration error across the income and wealth distribution:

$$(\hat{\alpha}_y, \hat{\alpha}_w, \hat{\gamma}_y, \hat{\gamma}_w) = \underset{\alpha_y, \alpha_w, \gamma_y, \gamma_w}{\arg\min} \sum_p \left| \widehat{MPC}_p - MPC_p^{target} \right| \tag{41}$$

where $\widehat{MPC}_p$ is the simulated MPC at percentile $p$ and $MPC_p^{target}$ is the corresponding empirical target. We conduct a fine grid search over all four parameters We conduct a fine grid search over all four parameters $(\alpha_y, \alpha_w, \gamma_y, \gamma_w)$ simultaneously, selecting the combination that produces the lowest average error across the distribution. Convergence is confirmed across iterations, and the distribution of errors across the full grid confirms a well-defined global minimum. Full grid search results and error diagnostics are provided in Appendix C.3.

### 4.3 Returns on Wealth

The return on wealth is calibrated to match empirical evidence on heterogeneity in returns across the wealth distribution (Bach, Calvet, & Sodini, 2020; Xavier, 2021; **?**). Given our expected return equation 21, which comprises of a fixed average annual return $(\bar{r})$, wealth-dependent return $(\phi \ln(1 + \frac{w_{i,t-1}}{W_{50}}))$, and a wealth-dependent volatility (equation 23). The wealth premium $\phi$ is calibrated to hit an empirical target of the return difference between the median households and the top 10. Studies have documented the return differences across the distribution. Fagereng et al. (2020) has demonstrated that moving from the $20th$ to the $90th$ percentile in the distribution of worth increases the return on wealth by $18\%$. Using data from the SCF, Xavier (2021) also found that on average, moving from the $20th$ to the $90th$ percentile of the wealth distribution increases yearly return from 3.6 to $8.3\%$. Other studies found a return difference between the median household and the top 10 between $2 - 4\%$ (Bach et al., 2020; Davis & Konstantinidis, 2024). Therefore, we targeted a return difference of $2\%$ between the median and top 10, by computing:

$$\phi = \frac{0.02}{[\ln(1 + \frac{W_{90}}{W_{50}}) - \ln(1 + \frac{W_{50}}{W_{50}})]} \tag{42}$$

Where the numerator is the percentage point gap return difference between wealth the top 10 and $50th$, while $W_{90}$ and $W_{50}$ are the estimated annual median wealth between the households in the $50th$ and top 10 of the wealth distribution, respectively. Therefore, this calibration process produces a $2\%$ return difference between the top 10 and the $50th$, which is held fixed across all individuals and generations in the simulation.

Additionally, the speed of volatility $(\psi)$ is also calibrated, such that if an individual reaches the median household level, they start to invest in riskier assets (such as stocks), thereby exposing them to more volatility. Evidence has documented that portfolio volatility increases rapidly in the middle of the wealth distribution, where households transition from safe assets to equity participation (Jones & Neelakantan, 2023). Therefore, assuming that volatility increases at the median, due to participation in riskier investments;

$$\sigma(W_{50}) = \sigma_{\min}^{vol} + 0.5 \cdot (\sigma_{\max}^{vol} - \sigma_{\min}^{vol}) \tag{43}$$

We therefore compute the value of the speed of volatility $(\psi)$ by using the equation:

$$\psi = \frac{\ln(2)}{\ln(1 + W_{50})} \tag{44}$$

However, we provide the full mathematical derivation of $\psi$ in appendix C.4.

| Parameter | Desc. | Value | Source |
|---|---|---|---|
| $H$ | Number of initial parent individuals | 3000 | |
| $T$ | Simulation periods | 100 | |
| $MC$ | Number of Monte Carlo Simulation | 200 | |
| Young | Proportion of young individuals | 0.20 | U.S. Census Bureau (2022) |
| Working | Proportion of working individuals | 0.63 | U.S. Census Bureau (2022) |
| Retired | Proportion of working individuals | 0.17 | U.S. Census Bureau (2022) |
| $A$ | Age-independent hazard rate | 0.00103 | Computed |
| $B$ | Age-dependent hazard rate | 0.00004 | Computed |
| $C$ | Rate of increase in the hazard with age | 0.087 | Computed |
| $a_0$ | Labour market entry and productivity age | 15 | |
| $a^r$ | Retirement age | 65 | |
| $G_W$ | Wealth Gini inequality for 2022 | 0.85 | WIID (2025) |
| $W_{90}$ | Annual median wealth of top 10 | $1301,000$ | Bennett, Hays, and Sullivan (2019) |
| $W_{50}$ | Annual median households wealth | $118,200$ | Bennett et al. (2019) |
| $\omega_0$ | Annual median earnings | $56,600$ | Bennett et al. (2019) |
| $\rho$ | Wealth and human capital correlation | 0.25 | |
| $\mu_{hc}$ | Mean of the initial human capital | 12 | U.S. Census Bureau (2020) |
| $\sigma_{hc}$ | Standard deviation of human capital | 2.5 | U.S. Census Bureau (2020) |
| $P^h - P^{ph}$ | High and Post-high school completion rate | $87 - 62\%$ | Hussar et al. (2020); Ma and Pender (2023) |
| $\beta_W^h - \beta_W^{ph}$ | Parental wealth effect on schooling | $0.07 - 0.25$ | Jay (2024); Sirin (2005) |
| $\beta_1$ | Effect of human capital | 0.10 | Card (2001); Patrinos (2024) |
| $\beta_2$ | Effect of experience | 0.06 | Polachek et al. (2008) |
| $\beta_3$ | Concavity of experiences | $-0.0010$ | Heckman, Lochner, and Todd (2006); Polachek et al. (2008) |
| $\sigma_\xi$ | Standard deviation of income shock | 0.20 | Cagetti and De Nardi (2008) |
| $\bar{r}$ | The average rate of return | 0.04 | Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019) |
| $\sigma^w_{min} - \sigma^w_{max}$ | Volatility of safe assets and riskier assets | $0.03 - 0.25$ | Bach et al. (2020) |
| $df$ | Degree of freedom | 8 | |
| $\psi$ | Speed of volatility | 0.145 | Computed |
| $\bar{c_y}$ | Maximum MPC out-of-income | 0.80 | Jappelli and Pistaferri (2014); Parker et al. (2013) |
| $\bar{c_w}$ | Maximum MPC out-of-wealth | 0.05 | Carroll et al. (2011) |
| $\alpha_y$ | Decline of consumption with income | 0.011 | Computed |
| $\alpha_w$ | Decline of consumption with wealth | 0.009 | Computed |
| $\gamma_y$ | Elasticity of mpy | 1.35 | Computed |
| $\gamma_w$ | Elasticity of mpw | 1.10 | Computed |
| $\iota_{rate}$ | Inheritance tax rates | $\in [0\%, 5\%, 15\%, 25\%, 50\% \& 75\%]$ | |

Table 1: Model parameters and values

## 5 Result and Discussion

The figure 2 presents the dynamics of the population across the simulation, justifying the periods of analysis. Our analysis starts from $t = 17$ to $t = 87$, covering a period of 71 years, which is strictly done because the model starts with one generation (parent generation), and during this initial period, the new generations (such as first, second and third) are not active in the labour market, which may cause bias in our inequality measurement. Thus, at the start of our analysis, the first generation is already active in the labour market, earns labour and starts to accumulate wealth. Additionally, given the overlapping generations, the periods beyond 83 shows a significant decline in the number of surviving individuals, which affects the timing of inheritances and the amount of transfers each surviving individual will receive from the redistribution mechanism. Therefore, we disregard periods after $t = 87$ when there was a large reduction in the total population, as shown in the population dynamics.

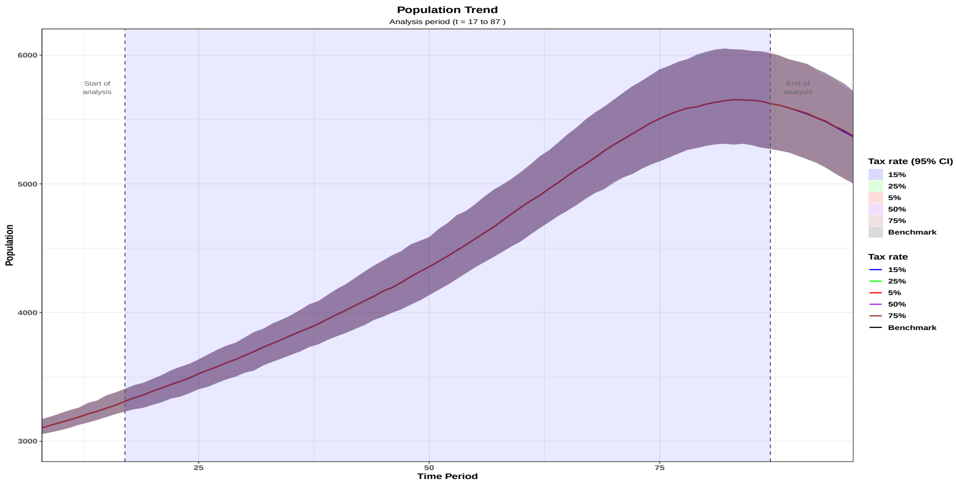



Figure 2: Population dynamic (Number of Surviving individuals at each time $t$)
Note: Median and 95% Monte Carlo uncertainty band across all MCs. At each $t$, the band shows the $2.5th$- $97.5th$ percentiles of the cross-simulation, not sampling errors. The vertical lines indicate the period of analysis.

This shows that the population size has evolved endogenously through the interplay of age-specific fertility and mortality rates. The initial rise in the population reflects the demographic transition as new generations enter the economy and start earning labour income to accumulate wealth, while at $t = 83$, the population peaks approximately at 5655 surviving individuals- indicates a demographic equilibrium.

The different tax rates do not affect the population dynamics, as the confidence intervals across these tax regimes and MCs overlap substantially; this demographic neutrality ensures that observed inequality patterns reflect redistributive effects and facilitate comparisons across tax regimes.

## 5.1 Descriptive Statistics of Inequality Measures

The descriptive statistics of wealth and consumption inequality, as shown in Table 2, reveal a striking pattern. Across all the different inheritance tax regimes, ranging from 0% (benchmark) to the highest rate of 75%, the mean and median values of wealth and consumption Gini decline with increasing tax rate.

For wealth Gini, under low inheritance tax regimes ($0 - 5\%$), median wealth Gini is greater than the mean (e.g. 0.687 vs 0.684)[10], indicating a mild left-skewness. With higher tax regimes ($15 - 75\%$), the mean wealth Gini exceeds the median (e.g. 0.670 vs 0.667), indicating a right-

[10] As mentioned earlier, the analysis of simulation begins when new generations enter the model. However, the initialised wealth (see appendix B.1) produces a Gini for wealth close to observed wealth

skewed distribution of wealth. As we have shown in figure 2, because the simulation produces identical demographics across all tax regimes, this divergence cannot be attributed to differing demographic randomness, but rather reflects the non-linear sensitivity of inequality indices to wealth shocks at different baseline compression levels. When tax regimes compress the wealth distribution, the same clustered inheritance or mortality events produce a larger proportional upward movement in the Gini, generating a pronounced right-tail realisation of the temporal Gini (mean exceed median).

In contrast, the consumption inequality remains lower across all inheritance tax rates; the median consumption Gini exceeds the mean at all tax regimes, indicating a left-skewed distribution in consumption, thus less inequality in consumption as the tax rate increases.

However, there is significant divergence between wealth and consumption inequality volatility. With equality enhancement tax regimes $(0 - 5\%)$, there is no change in relative volatility for both consumption and wealth inequality, while for tax rates above these, relative volatility of wealth inequality changes from $+0.004$ above the equality enhancement rates, which further increase non-linearly with progressive rates. The absolute and relative consumption Gini volatility is more stable, even though wealth becomes $3x$ more volatile under high taxes.

| | **Wealth Gini** | | | | **Consumption Gini** | | | |
|---|---|---|---|---|---|---|---|---|
| Tax Rate | Mean | Median | SD | CV | Mean | Median | SD | CV |
| 0% | 0.684 | 0.687 | 0.023 | 0.033 | 0.440 | 0.448 | 0.019 | 0.044 |
| 5% | 0.679 | 0.681 | 0.022 | 0.033 | 0.439 | 0.447 | 0.020 | 0.044 |
| 15% | 0.670 | 0.667 | 0.025 | 0.037 | 0.437 | 0.446 | 0.020 | 0.046 |
| 25% | 0.660 | 0.644 | 0.030 | 0.045 | 0.435 | 0.444 | 0.020 | 0.047 |
| 50% | 0.637 | 0.622 | 0.048 | 0.075 | 0.431 | 0.442 | 0.021 | 0.049 |
| 75% | 0.616 | 0.609 | 0.066 | 0.107 | 0.429 | 0.440 | 0.022 | 0.050 |

Table 2: Descriptive statistics of wealth and consumption Gini across all tax rates.

This aligns with both theoretical predictions and empirical patterns. Attanasio and Weber (1993) emphasises consumption smoothing due to credit market and precautionary savings, generating this effect. Our result shows just that: households use wealth as a buffer stock to smooth consumption (Attanasio, Banks, Meghir, & Weber, 1999; Carroll, 1997; Carroll, Hall, & Zeldes, 1992), thereby attenuating the transmission of wealth inequality into consumption inequality. The redistribution of wealth increases the consumption of the poorer household due to their higher marginal propensities to consume. Thus, progressive taxation creates unpredictable wealth outcomes but a predictable living standard.

### 5.2 Inequality Reduction Patterns

From our descriptive statistics, which show increasing volatility in wealth inequality with progressive taxation, while stable volatility in consumption. Now, observing the time trend of inequality dynamics presented in figure 3, a clear non-linear relationship is observed across tax regimes. The intensity of inequality reduction increases with the tax rate. From the periods of analysis, the tax regimes between $0 - 25\%$ reduces absolute wealth inequality up to a medium term, after which inequality starts to increase. An inheritance taxation and redistribution will have a greater effect in reducing inequality for tax regimes that are greater than $25\%$. In relative terms, inheritance tax will permanently reduce wealth inequality; however, the intensity of wealth inequality reduction is also greater for tax rates greater than $25\%$. This pattern aligns with Piketty and Saez (2013) optimal capital taxation theoretical framework. They demonstrated that taxes primarily affect the persistence of wealth inequality across generations rather than within-generation accumulation. Our result has shown this mechanism: as tax rates increase, the intergenerational transmission elasticity declines, reducing long-run wealth concentration. Additionally, other studies have demonstrated that inheritance in the short term reduces inequality, while in the long term, due to differences in savings across the distribution, it will increase inequality (Elinder et al., 2018; Morelli et al., 2025; Nekoei & Seim, 2023). Our framework captures this mechanism, lifecycle savings and stochastic returns continue to generate within-cohort inequality, and a punitive inheritance taxation can reduce wealth inequality, but with a cost of increasing economic volatility.

In contrast, consumption inequality also declines with tax rates, as higher inheritance taxation and redistribution reduce consumption inequality. However, the trend in consumption inequality increases during early periods, after a longer period around $t = 70$, consumption inequality falls, and the intensity of declining consumption inequality increases with the tax regime. In comparison with wealth, in the short-term, despite wealth inequality declining, the consumption inequality rises. This pattern reveals a lag in consumption response. By the period, $17 - 30$, progressive tax rates do not have any noticeable effect on consumption inequality, since the initial cohort is ageing, and inheritance taxes are collected from the dying elderly, which is distributed equally, thus wealth inequality falls immediately. The consumption distribution becomes very dispersed because the young workers consume very little, even with wealth transfers; they're saving, while the middle-aged consume a lot at their peak earnings and wealth accumulation stage (Kotlikoff, 1988; Modigliani, 1988), which increases consumption inequality temporarily. This mechanism confirms that consumption responds slowly to wealth distribution, and lifecycle effects dampen the consumption response. Over time, consumption inequality falls due to demographic equilibrium, as old generations are being replaced by the new generation and their consumption patterns reflect a more equal wealth distribution, the early transfers saved by the young are now consume at middle-aged individuals. This implies that equalising effects accumulate over generational timescales rather than appearing immediately. All tax regimes initially show a decrease in wealth inequality, while an increase in consumption inequality. The $75\%$ tax regime demonstrates a sustained reduction after approximately a period of $50$, which underscores that inheritance taxation policies require patience and persistence to achieve their full distributional benefits. This systematic improvement across tax rates demonstrates the scalability of inheritance taxation as an inequality-reduction tool. The increasing inequality under the benchmark scenario exemplifies the $r > g$ dynamics described by (Piketty, 2014), where inherited wealth compounds faster than economic growth, naturally leading to concentration.

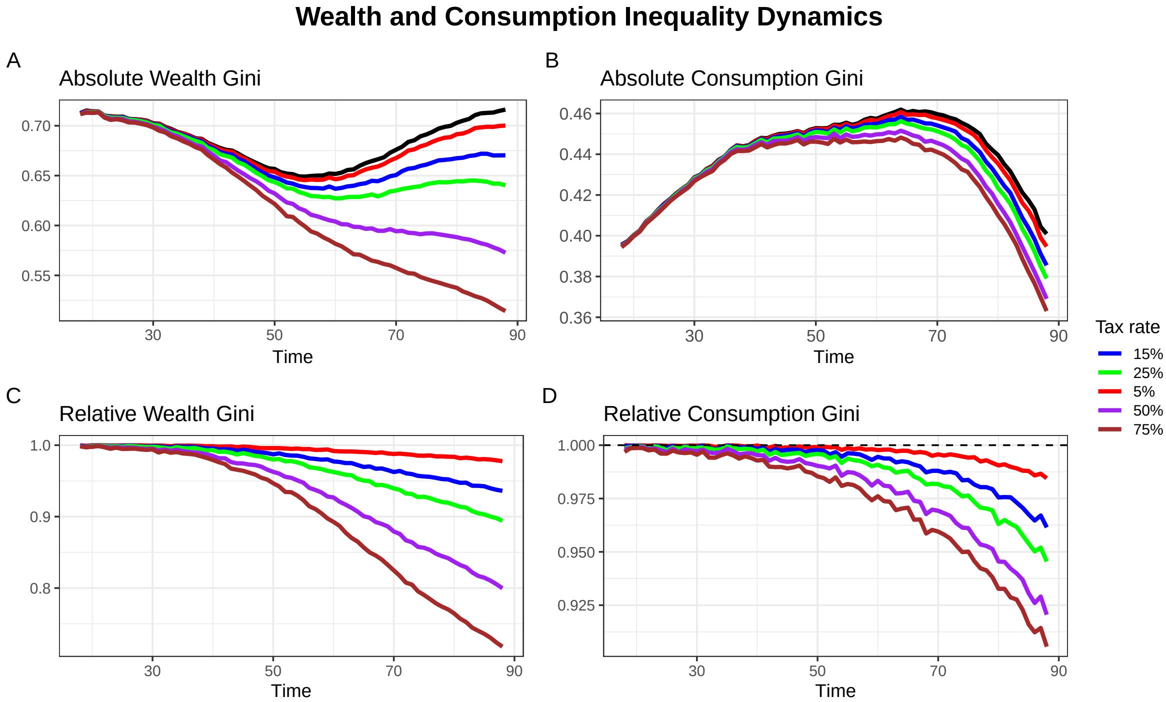



Figure 3: Wealth and Consumption Gini (Absolute vs Relative) trends

## 5.3 Aggregate Wealth Preservation

The debate on inheritance taxation is often centred on the equity-efficiency trade-off (Cowell et al., 2018; Piketty & Saez, 2013), reducing inequality comes with a cost of reducing aggregate economic capital accumulation, due to behavioural response by heirs and testators, who may prefer leaving inter vivos, especially if leaving bequests are seen as a "warm-glow". Our results do not show any absolute aggregate wealth deduction in a closed economy; inheritance taxes and redistribution do not have a noticeable difference in increasing aggregate wealth, since all the inheritance taxes and unclaimed wealth are fully distributed (i.e. no wealth loss) to all surviving individuals, which are used to improve consumption and human capital accumulation to increase the earnings of children. An increasing inheritance tax lowers inequality without significantly affecting absolute aggregate wealth, even after factoring in demographic changes.

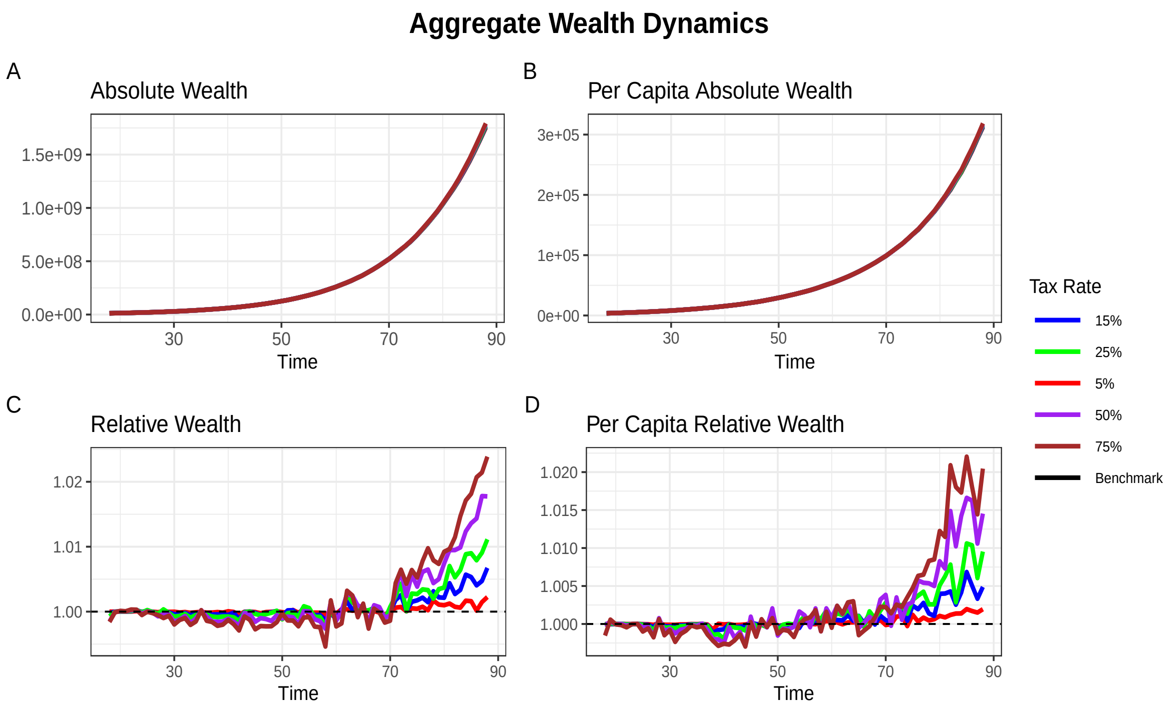



Figure 4: Aggregate wealth

However, in relative terms, progressive taxation will slightly lower aggregate wealth in the short to medium term, since it reduces the capital accumulation of the wealthier households. Over the medium-term, since inheritance taxes are distributed, which act as both predistribution and redistribution, enabling poorer households to invest in human capital accumulation of their children to increase their productivity in the labour market, which then translates to higher earnings and savings to accumulate wealth. Therefore, despite progressive inheritance taxation reducing absolute wealth inequality over time, it has no significant effect on absolute aggregate wealth. The effect of taxation, in relative terms, reduces wealth inequality. Its effect on aggregate wealth accumulation occurs in the long-term, when redistributions are used to promote human capital development.

Furthermore, our result shows an interesting pattern. Despite inheritance taxation having a small effect on absolute aggregate wealth, it has a positive effect on relative aggregate wealth in the medium-term. When we disaggregate households into percentiles, we found that inheritance taxation and redistribution over the medium term reduce the total wealth accumulation of the top 1 and top 10, despite increasing the aggregate wealth accumulation of the bottom 50, both in relative and absolute terms, as depicted in figure 5.

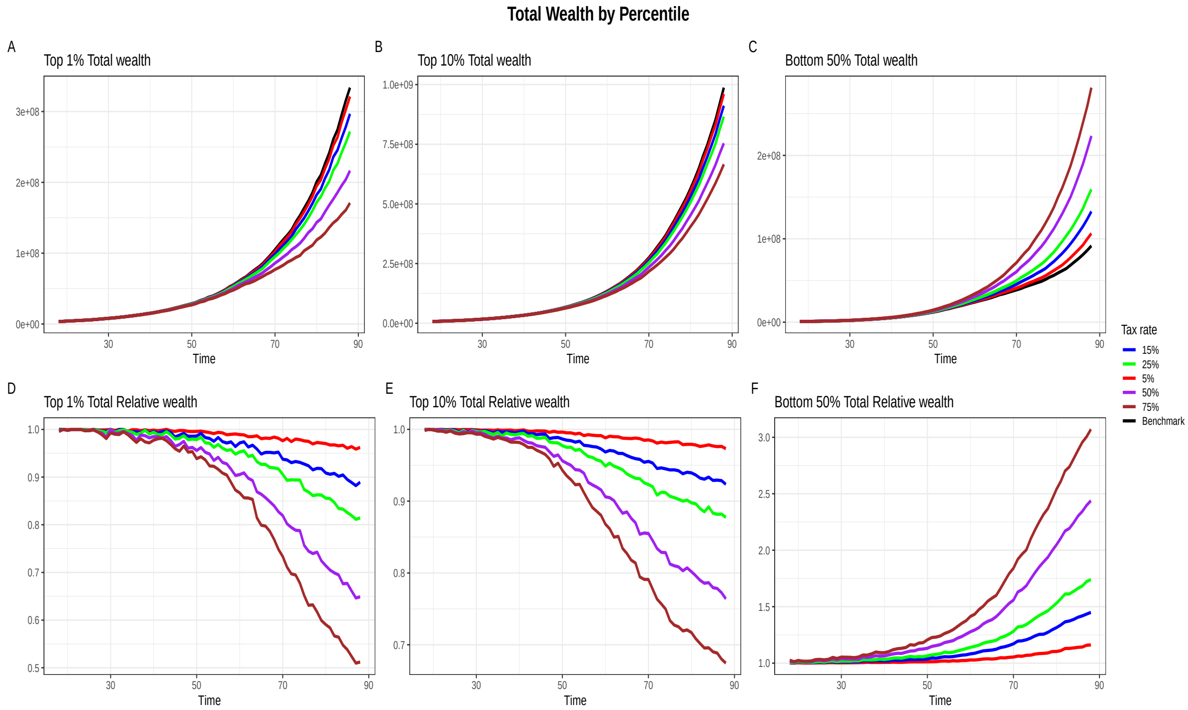



Figure 5: Aggregate wealth by percentile groups

The progressive inheritance taxation of wealthier households reduces the amount of transfers they leave to their heirs, and thus reduces their capital accumulation. This evidence is in tandem with theories of inheritance taxation (Cowell et al., 2018; Galle et al., 2025; Piketty & Saez, 2013). When these taxes are distributed, they immediately improve the relative wealth of poor households. However, their effect on their wealth accumulation takes effect in the medium-term, when these households finance the human capital development, to enhance their labour market productivity and earnings to accumulate more wealth. This also aligns with Galor and Zeira (1993) demonstration: with credit constraints, poor households may not be able to finance human capital development, leading to lower steady-state growth and increasing inequality.

### 5.4 Shares by percentiles

Table 3 shows a clear redistributive story. Without inheritance tax, the Bottom 50 holds just 7.80% of total wealth shares. In contrast, the Top 10% and Top 1% hold 55.08% and 23.01% respectively, indicating a stark concentration. As taxes rise to 75%, the Bottom 50% gains roughly 3.6 percentage points, while the Top 10% and Top 1% lose 6.38 and 3.00 percentage points, respectively. This confirms that inheritance taxation redistributes wealth downward. Notably, the Top 10% absorbs the largest relative loss, suggesting the broader wealthy class is more exposed to redistribution than the super-rich alone.

Beyond the averages, the shape of each group's distribution shifts in interesting ways. At low tax rates, the top 1% means exceeds the median, meaning a handful of extremely wealthy households inflate the average. At 50% and 75% taxes, this flips, indicating that high taxation compresses the very top. For the Bottom 50, the picture is messier: at a higher tax rate, most households cluster at higher shares, but few with very low shares pull the mean below the median, suggesting redistributive benefits are not evenly spread within the groups.

Perhaps most telling is the growing spread at the top. The Top 10% IQR more than triples from 4.13 to 15.32 as taxes rise, which implies that, while average shares fall, outcomes become increasingly unpredictable across simulations. The Bottom 50%, by contrast, shows relatively stable dispersion throughout. In a nutshell, progressive inheritance taxation narrows the gap between rich and poor in terms of wealth shares, but makes outcomes at the top considerably more uncertain.

In contrast, the consumption shares table 4 reveals a fundamentally different picture from wealth. Even without any inheritance tax, the Bottom 50% already holds 16.86% of total consumption, which is more than double their 7.80% wealth share — while the Top 1% holds just 3.49%, confirming that consumption is far more equally distributed than wealth from the outset. As taxes rise to 75%, the redistributive effects on consumption are notably muted: the Bottom 50 gains only 1.23 percentage points, the Top 10 loses just 0.43 points, and the Top 1 share barely moves at all (3.49% to 3.52%), suggesting wealthy households absorb inheritance tax shocks through their wealth stock rather than cutting consumption — consistent with (Attanasio & Weber, 1993) consumption smoothing framework. The distributional shape reinforces this: the Bottom 50 is right-skewed throughout (mean exceeds median), reflecting lifecycle effects where middle-aged households consume more, while the Top 10 and Top 1 remain left-skewed at all tax rates. Most telling is the stability of dispersion — unlike wealth, where the Top 10 IQR triples from 4.13 to 15.32, consumption IQR and SD remain almost entirely unchanged across all groups and tax rates, confirming that progressive inheritance taxation creates volatile wealth outcomes but leaves living standards largely predictable, with its equalising effects on consumption being real but modest and slow-moving.

Furthermore, Figure 6 presents the dynamics of wealth shares across time. Shows differences in wealth shares between these groups across tax regimes. For the top 1 and the top 10%, their wealth shares decline with progressive tax rates, both in relative and absolute terms. The top 1% absolute shares decline monotonically for a tax rate of greater than 25%. The decline in absolute shares is lower, compared to the top 10%, who sees a significant decline in their absolute shares for a tax rate greater than 25%. However, without inheritance taxation, redistribution will benefit the bottom 50% for the short-term, but over the medium-term, their shares will significantly decline, while the wealthy's shares will increase, due to differences in consumption and savings patterns-the bottom 50% will consume a larger part of their wealth, due to their higher marginal propensity to consume, while the wealthier will save a significant part of their wealth to accumulate more wealth.

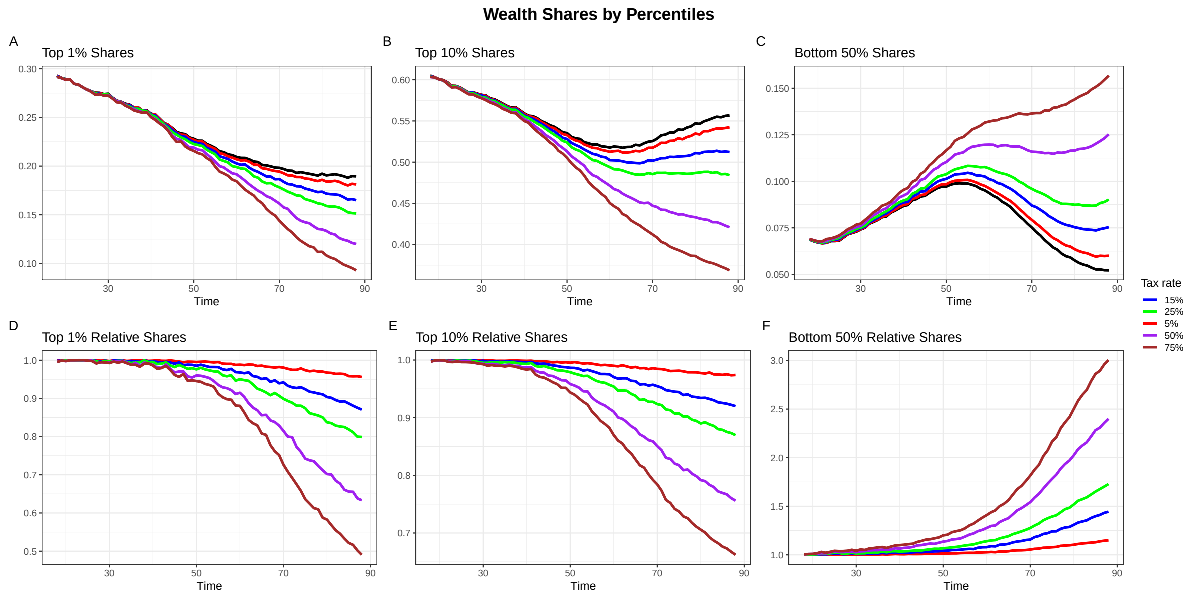



Figure 6: Households' wealth shares by percentiles

Progressive taxation and redistribution will have two effects on the economy: first, it will reduce the wealth accumulation of the wealthier households, and second, it will enable the poor to finance the human capital development to increase earnings capabilities, which is exactly the redistribution and predistribution demonstrated by (Cowell et al., 2018), this overtime will improve their position in wealth distribution. Additionally, the interquartile range shows in table 4 that the bottom $50$ wealth share outcomes reduce from $2.40$ at the benchmark to $1.87$ at $25\%$, implying that moderate taxation will make their shares more concentrated around the median. However, at higher taxes $(50 - 75\%)$, interquartile significantly increases to $4.93$ and volatility rises from $1.46$ to $2.84$, meaning that, despite the bottom $50$ gaining with redistribution, their shares become much more erratic; in some periods they hold large shares, while holding less in other periods. The increasing volatility reflects that when wealth is evenly distributed, the same random shocks (such as inheritances, mortality or investment returns) produce large swings in the bottom shares. This indicates a key trade-off with progressive taxation: it reduces average concentration but introduces greater volatility in the wealth of all groups. The bottom $50$ experience more variable gains, while the top groups face substantially more uncertainty in their relative position. This instability is a consequence of compressing the wealth distribution in a stochastic environment; random events will have a large effect when underlying disparities are smaller.

Furthermore, the timing of these tax regimes is also crucial. Studies have demonstrated that inheritances will boost the relative and absolute wealth of the poorer households immediately they are received, while for the wealthier households, since inheritances form a small portion of their wealth, they will not have a significant effect. However, in the long-term, due to differences in savings between these household groups, it will drive inequality in the longer-term (Elinder et al., 2018; Karagiannaki, 2017; Nekoei & Seim, 2023).

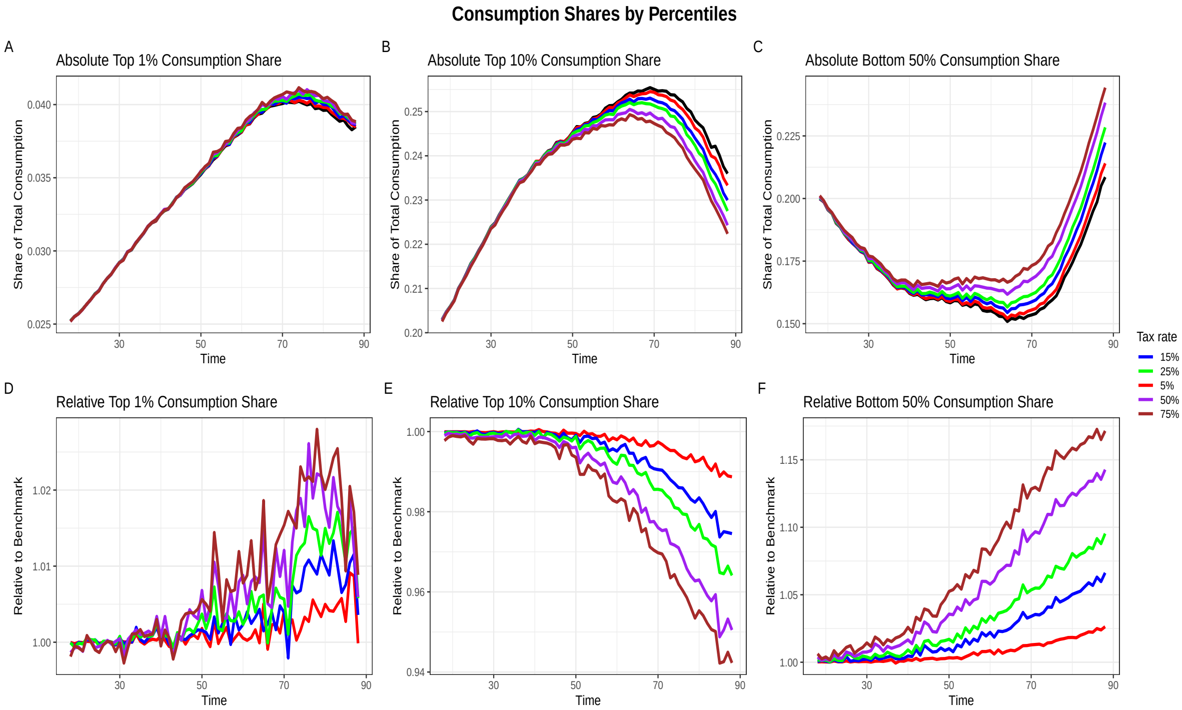



Figure 7: Consumption shares of households by group (absolute vs relative)

When we observed the timing at which inheritance taxation and distribution will affect household groups, as presented in figure 14, we see clear evidence of periodic patterns. For the first 25 years of which inheritance taxation and redistribution occur, the different tax regimes do not have any noticeable effect in reducing the wealth shares of wealthy households. Their effects, after the first 25 years, start to reflect on wealth shares of household groups, but the effects are minimal. Inheritance taxation and redistribution start to have a significant effect on reducing households' wealth shares after 50 years-when households use their inheritances to enhance human capital development and earning abilities to accumulate wealth. Before the first 50 years, poorer households consume and invest a large part of windfalls, the investment in human capital accumulation of their children increases the wealth earnings and accumulations of the future generation.

Taxation and redistributional policies immediately improve consumption of poor households, both in relative and absolute terms, since they have a higher marginal propensity to consume. By contrast, for the wealthier households, wealth acts as a buffer; the different tax policy regimes will not have any effect on their consumption, it will only have an effect on their relative consumption shares, which is very unpredictable for the wealthiest (top 1). Inheritance tax regimes will only affect the consumption of wealthy households over the long-term, when taxes reduce their wealth accumulation.

Finally, we now examine the shares of each household group in each tax regime. As presented in figure 11 and figure 12, with a tax rate of between $0-25\%$, there is no noticeable improvement in the shares of the bottom 50, while the wealthy almost maintained their wealth shares. However, at tax rates greater than $25\%$ there has been a significant improvement in the shares of the bottom $50$, which is significant;y starts to increase, while the shares of the wealthy, decline significantly. In contrast, for consumption shares of the percentile groups, the top $10$ and bottom $50$ consumes significant amount of their windfalls, across all tax rates. Despite the progressive tax rates, there hasn't been any noticeable difference across the tax regimes.

## 6 Sensitivity Analysis

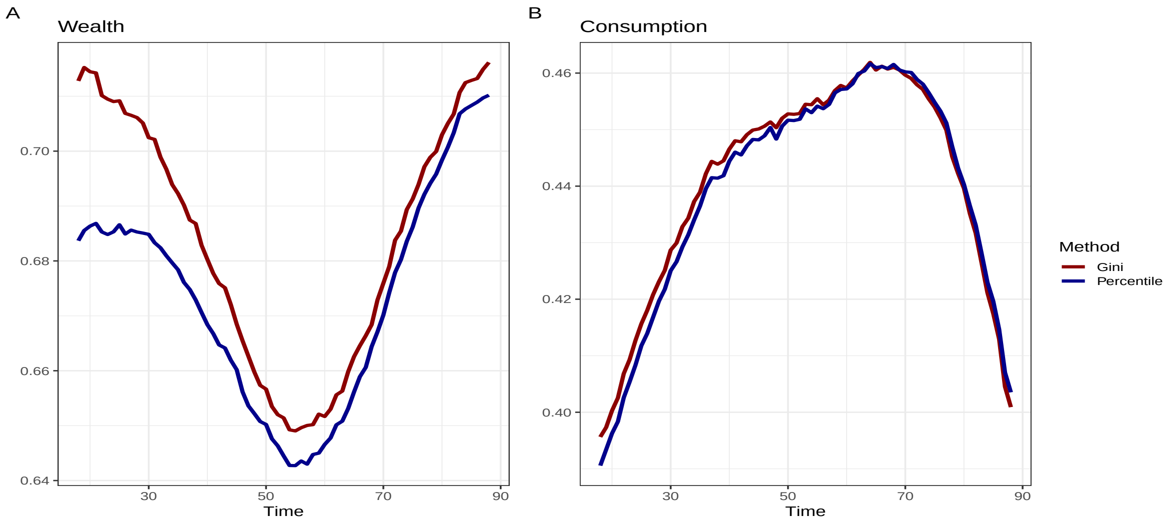
A key aspect and challenge of computational models is how the outcomes of the model change with respect to changes in some parameters of the model, especially a large-scale agent-based model of this nature-this determine the stability of this model when some parameters change. In this section, we examine how the result of our simulation will change when the initialisation of wealth and human capital of the parent generation is changed. The initialisation of the parent generation determines their wealth at $t = 1$, which will have a different accumulation process due to the wealth premium and volatility that rise with wealth. As we demonstrated in the initialisation of wealth and human capital in appendix B, so far, the results and discussions of the simulation result are based on the Gini initialisation method. Instead, we now initialise wealth using a percentile-based approach. In this latter initialisation, we derive the log-normal standard deviation from the estimated annual wealth of the top $10$ and median households $W_{50}$[11]. While the former derived the log-normal standard deviation from the target Gini coefficient $G_W$ (assuming wealth is log-normally distributed in both).

In a nutshell, these two initialisation methods differ significantly. The former produces an initial wealth distribution that will result in a Gini wealth inequality of the target $G_W$. Thus, it helps to capture the overall wealth distribution. The percentile-based method uses the estimated median wealth and the top $10$ wealth to generate an initial wealth distribution with exactly a median wealth of the target $(W_{50})$, thus it helps to capture wealth concentration at the top.

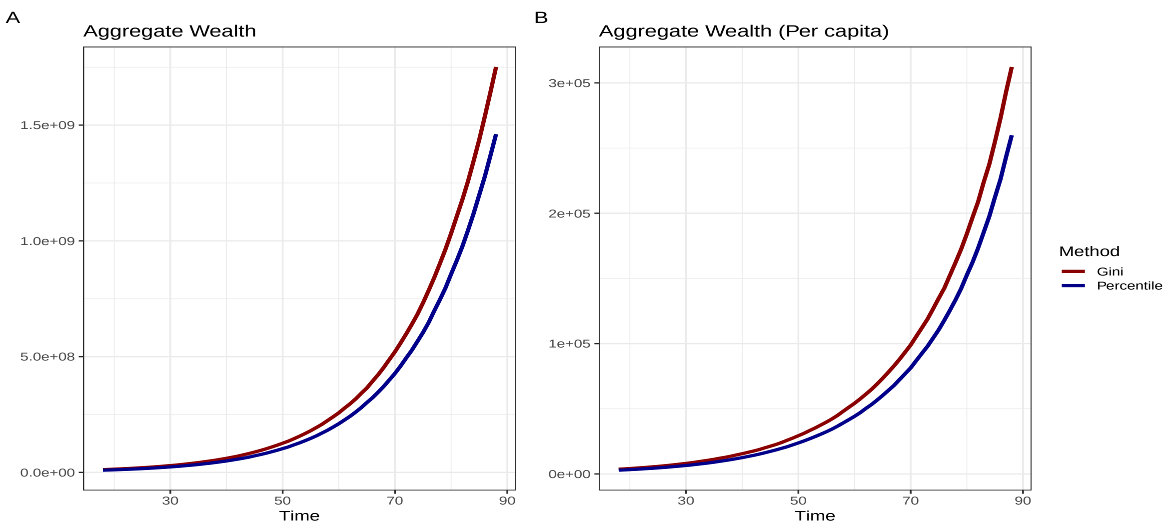
The nature of the initial wealth distribution dictates the starting state of the path-dependent dynamic (such as wealth, accumulation and inheritance). The tail of the distribution of wealth is often found to be Pareto (Benhabib & Bisin, 2018; Cowell, 2011). This former method produces a fatter tail for the initial wealth at $t = 1$[12], which implies that over time, it determines the importance of inheritance, and if death occurs earlier, it creates a significant amount of revenue for inheritance tax and redistribution. Therefore, given the importance of the initial wealth distribution, we run the simulation, using the same parameters as the former simulation, then compare the benchmark result of the Gini-based initialisation to examine how the dynamics of the aggregate variables, inequality, and shares change over time. Figure 8 shows that both initialisation method produces the same dynamics of wealth and consumption inequality over time, as well as the aggregate wealth in both absolute and per capita. However, the magnitude

[11] See appendix B.2, the mathematical derivation of the log-normal parameters from the percentile-based method.
[12] The standard deviation of the Gini log-normal conversion is greater than the percentile-based conversion

differs for Gini inequality measures. The former method produces an initially higher wealth inequality, but over time, it almost converges to the same path. This Gini method also produces a slightly higher wealth accumulation in both absolute and per capita terms. For consumption inequality, it also produces a very tiny higher inequality, which dissipates over time.



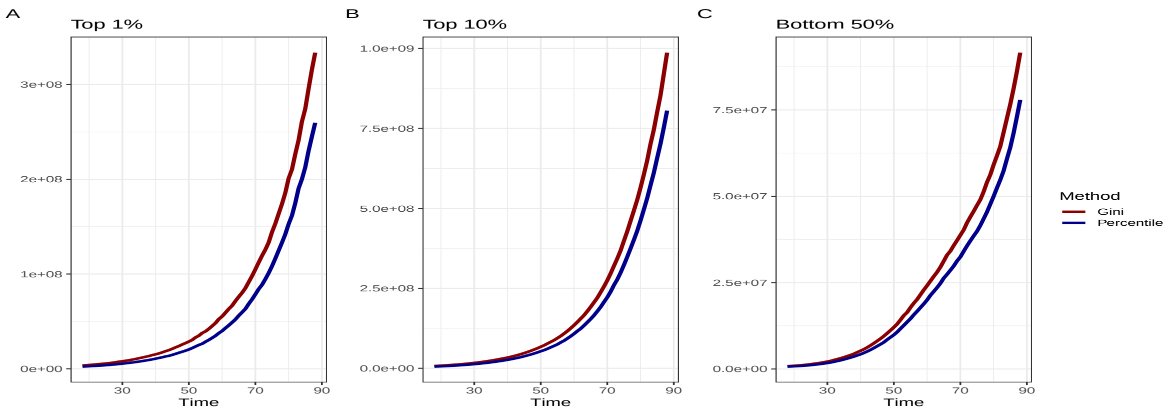

(a)



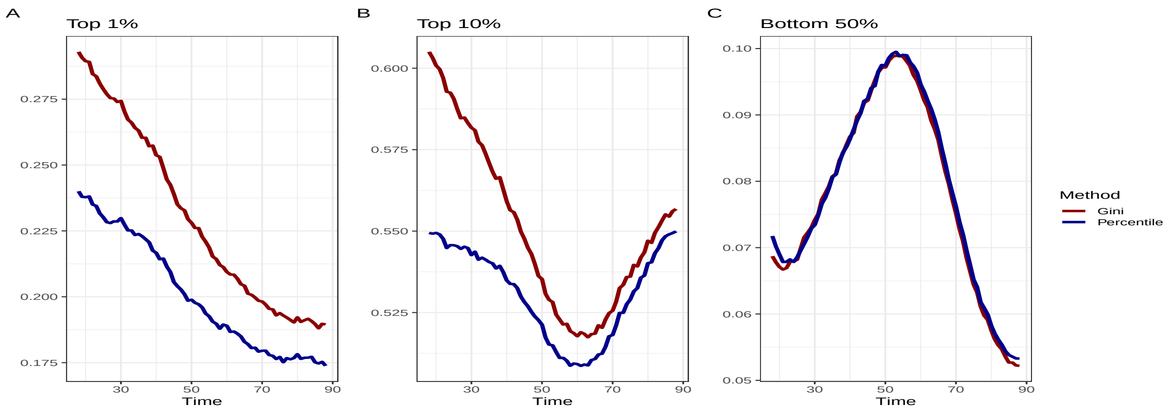

(b)

Figure 8: (a): Compares wealth and consumption inequality dynamics.
(**b**): Compares the absolute and per capita wealth aggregates.

Additionally, when we observed the aggregate wealth by percentiles, as presented in figure 9, the Gini-based method consistently produces a higher wealth for the top 1, top 10 and the bottom 50 households' total wealth, only slightly higher than the percentile method. While in terms of percentile shares, the Gini method produces a more significant share for the top 1 and top 10, with a very tiny difference initially, which remains the same after.



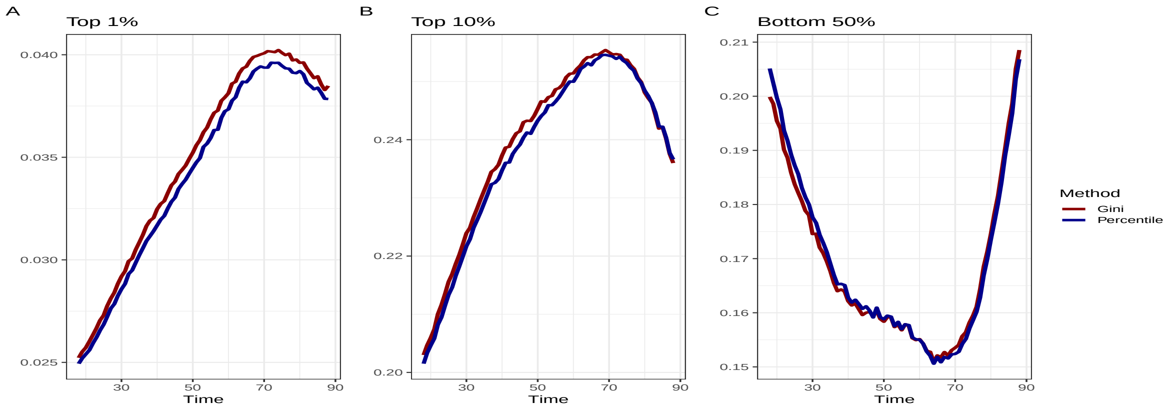

(a)



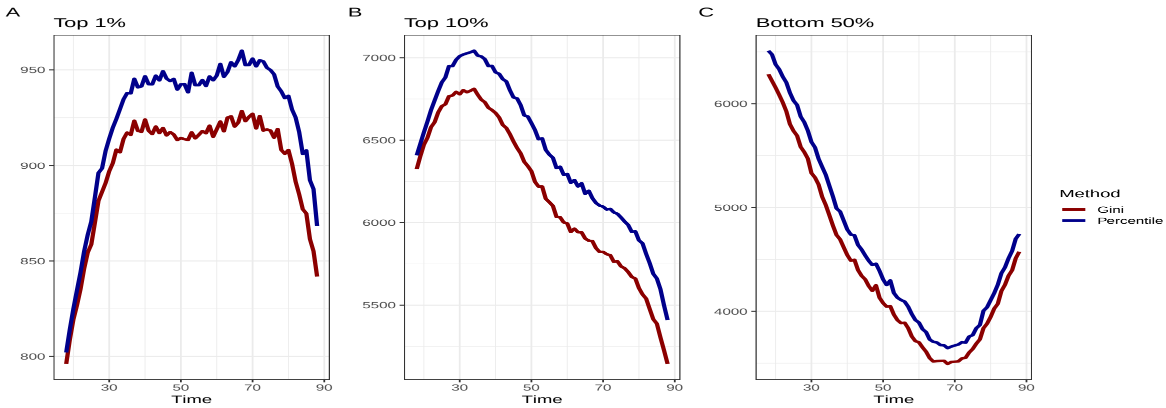

(b)

Figure 9: (a): Total (absolute) wealth by households groups.
(**b**): Wealth shares (relative) by household groups.

Finally, figure 10 consumption shares and total household consumption by household groups also reveals similar pattern. The Gini-based method produces slightly higher consumption shares of the top 1 and the top 10, while the consumption share of the bottom 50 almost the same in the two initialisation methods.




(a)




(b)

Figure 10: Comparison of consumption measures across methods and groups.

Despite the differences in how the two initialisation methods target the wealth distribution—one anchoring to the overall Gini coefficient, the other to the median and top 10 wealth-both produce similar dynamics over time. The Gini-based method starts from a higher level of wealth inequality and a fatter distributional tail, which generates more inheritance tax revenue early on and slightly higher wealth accumulation. Yet these initial differences dissipate as the simulation progresses; the trajectories of wealth inequality, consumption inequality, and aggregate wealth converge toward the same path regardless of where the simulation begins. The same pattern holds at the percentile level — the Gini method produces marginally higher shares for the top 1 and top 10 initially, but the gap narrows and stabilises over time. This convergence is reassuring: it suggests that the model's core mechanism is robust to the choice of initialisation, and that the dynamics of wealth accumulation and intergenerational transmission are driven by the structural features of the model rather than its starting conditions. In that sense, the sensitivity analysis confirms that the main results are not an artefact of how wealth is initialised.

## 7 Conclusion

Inheritance taxation sits at the centre of a debate about whether reducing inequality necessarily comes at the cost of economic efficiency. Most of the existing literature treats this as an either/or question, and much of it focuses on short-run behavioural responses-whether testators shift to inter vivos giving, or whether heirs reduce labour supply without asking what happens to wealth and consumption dynamics over a generation or more.

This study takes a longer-term dynastic approach: The model incorporates stochastic, dynamic and heterogeneous demographic and returns on wealth, wealth-dependent educational outcomes, and heterogeneous consumption patterns, providing a framework for examining how inheritance taxation and redistribution ripple through the wealth distribution over time. What emerges is a more nuanced picture than the standard trade-off narrative suggests.

Wealth inequality responds to inheritance taxation in a non-linear way. Rates up to $25\%$ produce only a temporary reduction in the Gini coefficient: the underlying forces of wealth concentration, such as the differences in savings rates, stochastic returns, and intergenerational transmission, eventually reassert themselves. It is only above $25\%$, and mostly clearly at $75\%$, that taxation produces a sustained and absolute decline in wealth inequality. The skewness of the Gini shifts from left to right as tax rates rise, reflecting the fact that rare, large inheritances carry more distributional weight when the baseline wealth distribution is already compressed. However, consumption inequality behaves quite differently. It declines monotonically with the tax rate but modestly, and its distribution remains left-skewed throughout. In the short-run, consumption inequality can actually rise while wealth inequality falls, a lag that reflects lifecycle behaviours. Transfers received by younger households are largely saved; it is middle-aged households who consume at their peak, widening the consumption distribution temporarily, before the wealth of younger cohorts eventually feeds through into spending.

The efficiency concern that taxing inheritances reduces aggregate capital does not materialise in this framework, and the reason is straightforward: all tax revenue and unclaimed bequests are fully redistributed, so no wealth leaves the economy. In absolute terms, the total capital stock is preserved. A modest relative trade-off does appear in the early decades as wealthy households accumulate less, but it dissipates as redistributed funds finance human capital investment among lower-income households, raising their productivity and saving capacity over time. Disaggregating by percentile makes this concrete: the top 1 and top 10 lose both wealth share and absolute wealth under progressive taxation, while the bottom 50 gain in both dimensions. However, this redistribution does not come without cost. As the wealth distribution compresses, the same random events, an unusually large inheritance, a cluster of deaths, a run of poor investment returns, produce much larger swings in the Gini than they would under a more dispersed distribution. Wealth outcomes become roughly three times more volatile at the highest tax rates, even as consumption remains stable. The efficiency cost of inheritance taxation, in other words, is not lost capital — it is a more turbulent wealth distribution, where compression amplifies the effect of shocks that were always there.

The timing, however, is everything. In the first 25 years of a reform, the wealth shares of the affluent are barely touched. The combined effect of reduced bequests at the top and improved human capital at the bottom only becomes clearly visible after roughly half a century, when the children of the initial recipient generation reach their peak earning years. Wealthy households do not adjust their consumption until their wealth accumulation itself begins to fall, treating bequest taxation as a levy on transfers rather than on their own lifetime resources.

This long gestation period has clear implications for the political cycle. Policies whose distributive gains materialise only over decades are unlikely to generate immediate electoral rewards, even if their long-run effects are substantial. As a result, sustaining such reforms would require a shared, cross-partisan commitment to foundational objectives—such as broad access to quality education, equality of opportunity, and social sustainability—extending beyond short-term political incentives and electoral horizons.

Taken together, these findings suggest that the equity-efficiency trade-off, long treated as an inevitable cost of inheritance taxation, is substantially weakened when tax revenues are recycled in ways that build the productive capacity of the next generation. Pre-distribution — using transfers to alter the starting conditions of the poor, rather than simply compensating them after the fact, is what drives this result. The policy implication is not complicated, but it does require patience: inheritance taxation works, but its benefits accumulate over generational timescales, not electoral cycles. What this study ultimately shows is that the real trade-off is not between equality and efficiency. It is between the short-term political difficulty of sustaining such a policy and the long-term distributional gains that follow when it is.

# A Additional Results

## A.1 Further descriptive statistics for wealth and consumption shares by percentile groups

| | **Bottom 50%** | | | | **Top 10%** | | | | **Top 1%** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tax | Mean | Median | IQR | SD | Mean | Median | IQR | SD | Mean | Median | IQR | SD |
| 0% | 7.80 | 7.82 | 2.40 | 1.46 | 55.08 | 54.70 | 4.13 | 2.60 | 23.01 | 22.28 | 6.41 | 3.44 |
| 5% | 8.05 | 7.95 | 2.45 | 1.34 | 54.60 | 53.76 | 4.65 | 2.86 | 22.77 | 22.18 | 6.80 | 3.66 |
| 15% | 8.54 | 8.45 | 2.21 | 1.22 | 53.65 | 51.86 | 6.12 | 3.49 | 22.30 | 21.89 | 7.59 | 4.10 |
| 25% | 9.04 | 8.98 | 1.87 | 1.26 | 52.73 | 51.35 | 8.03 | 4.22 | 21.86 | 21.69 | 8.29 | 4.53 |
| 50% | 10.24 | 11.48 | 3.28 | 1.91 | 50.55 | 49.96 | 11.84 | 6.13 | 20.86 | 21.24 | 9.97 | 5.50 |
| 75% | 11.38 | 12.31 | 4.93 | 2.82 | 48.70 | 49.00 | 15.32 | 7.93 | 20.01 | 20.83 | 11.68 | 6.41 |

Table 3: Wealth shares with distributional statistics (% of total wealth) for each household group across tax rates.

| | **Bottom 50%** | | | | **Top 10%** | | | | **Top 1%** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tax | Mean | Median | IQR | SD | Mean | Median | IQR | SD | Mean | Median | IQR | SD |
| 0% | 16.86 | 16.17 | 2.11 | 1.53 | 23.94 | 24.33 | 1.93 | 1.48 | 3.49 | 3.62 | 0.83 | 0.48 |
| 5% | 16.99 | 16.24 | 2.15 | 1.58 | 23.88 | 24.31 | 1.86 | 1.45 | 3.49 | 3.63 | 0.84 | 0.49 |
| 15% | 17.21 | 16.44 | 2.15 | 1.65 | 23.79 | 24.26 | 1.88 | 1.41 | 3.50 | 3.63 | 0.85 | 0.49 |
| 25% | 17.40 | 16.50 | 2.20 | 1.72 | 23.73 | 24.11 | 1.90 | 1.38 | 3.51 | 3.65 | 0.86 | 0.50 |
| 50% | 17.78 | 16.90 | 2.13 | 1.85 | 23.60 | 24.06 | 1.86 | 1.32 | 3.51 | 3.66 | 0.88 | 0.51 |
| 75% | 18.09 | 17.21 | 2.10 | 1.92 | 23.51 | 23.94 | 1.86 | 1.29 | 3.52 | 3.67 | 0.89 | 0.51 |

Table 4: Consumption shares with distributional statistics (in %). Unlike wealth shares, consumption exhibits modest redistribution: bottom 50% share rises, while top 10% declines and top 1% share remains flat, confirming consumption smoothing by wealthy households

## A.2 Wealth Shares Across Tax Regime

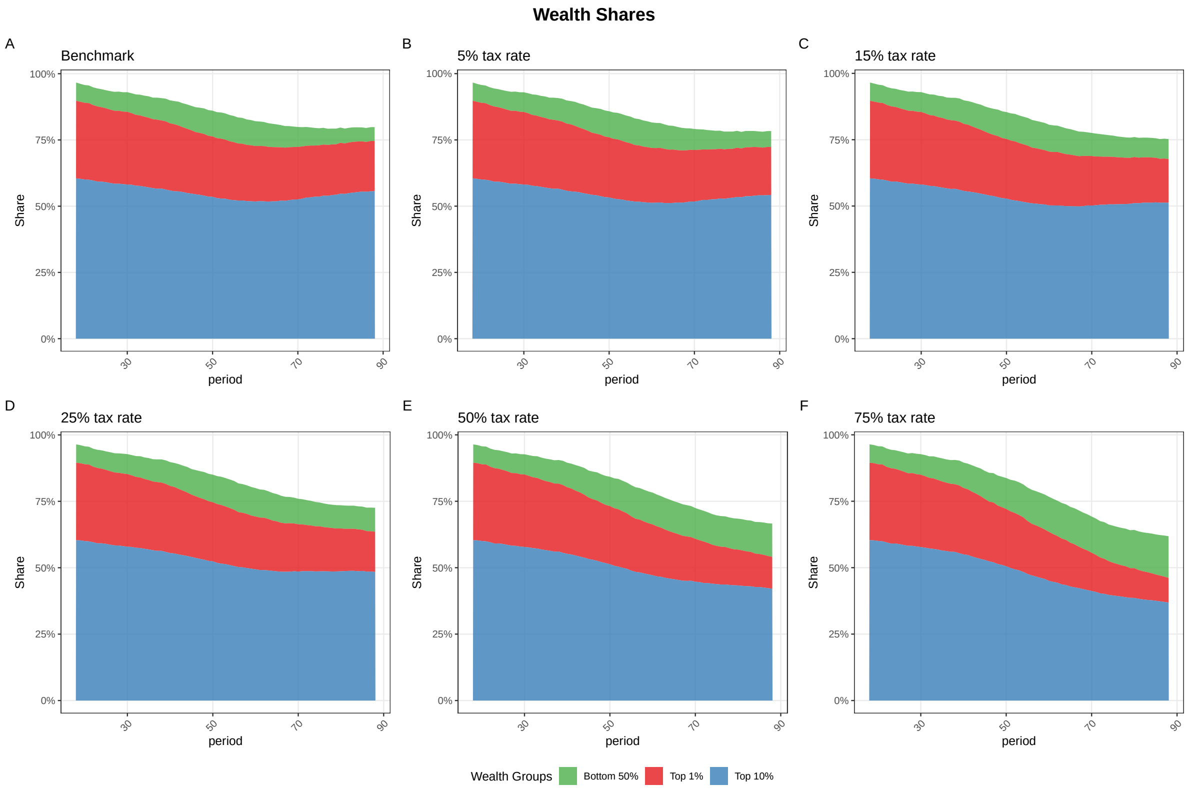



Figure 11: Distribution of shares by percentiles within each tax regime

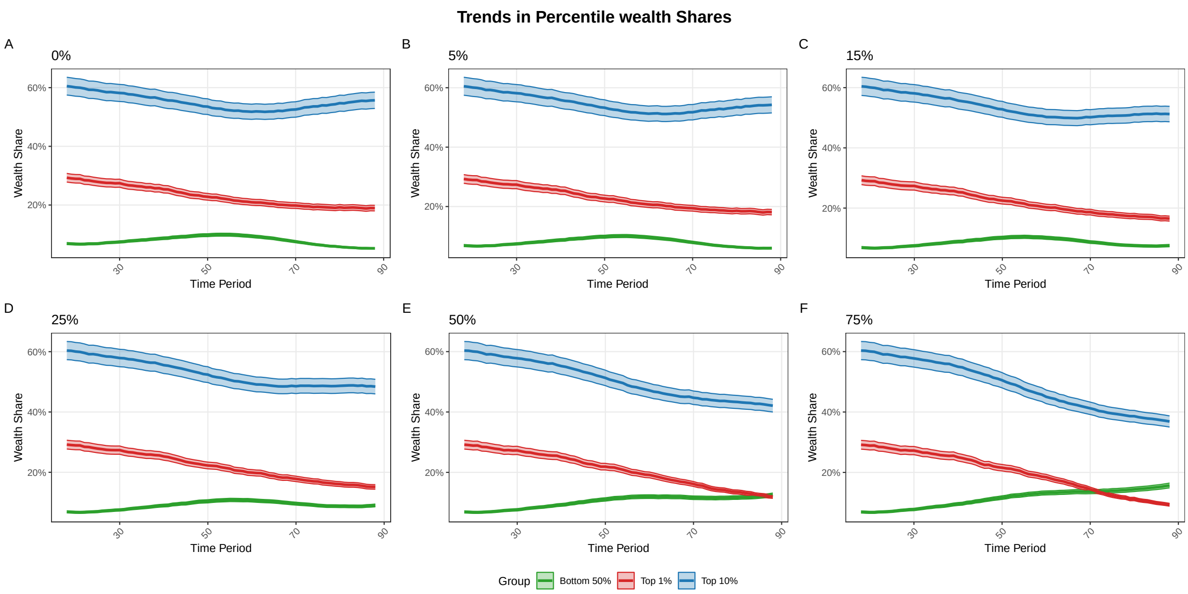



Figure 12: The trend in wealth shares by percentile groups within each tax regime

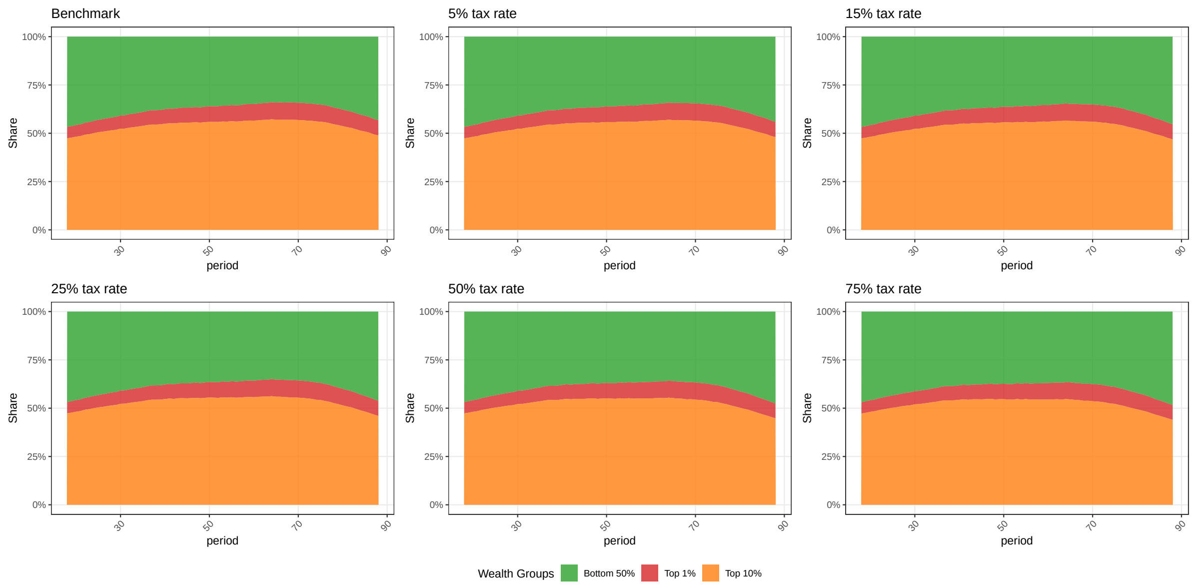
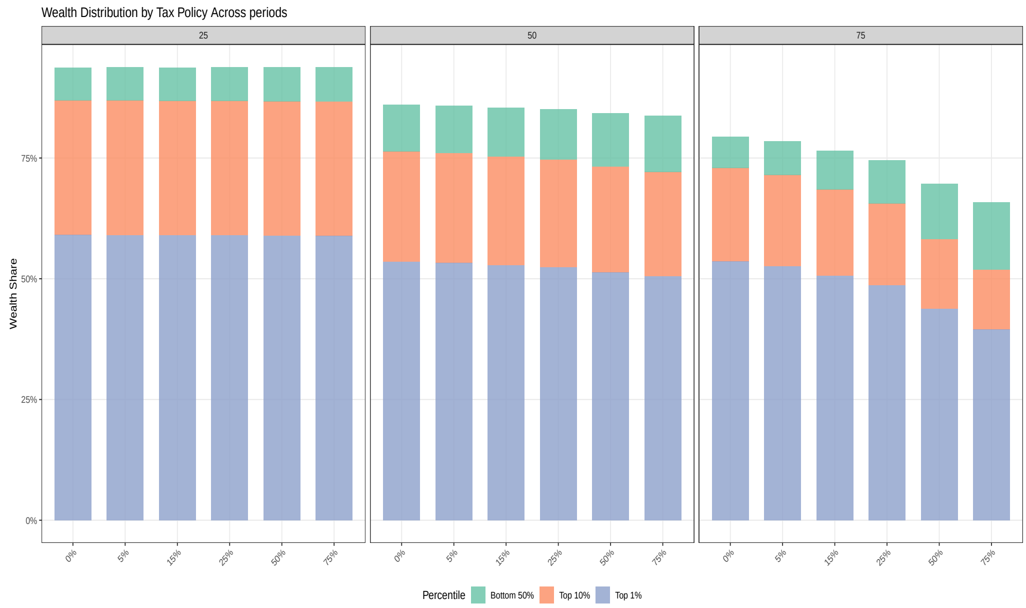
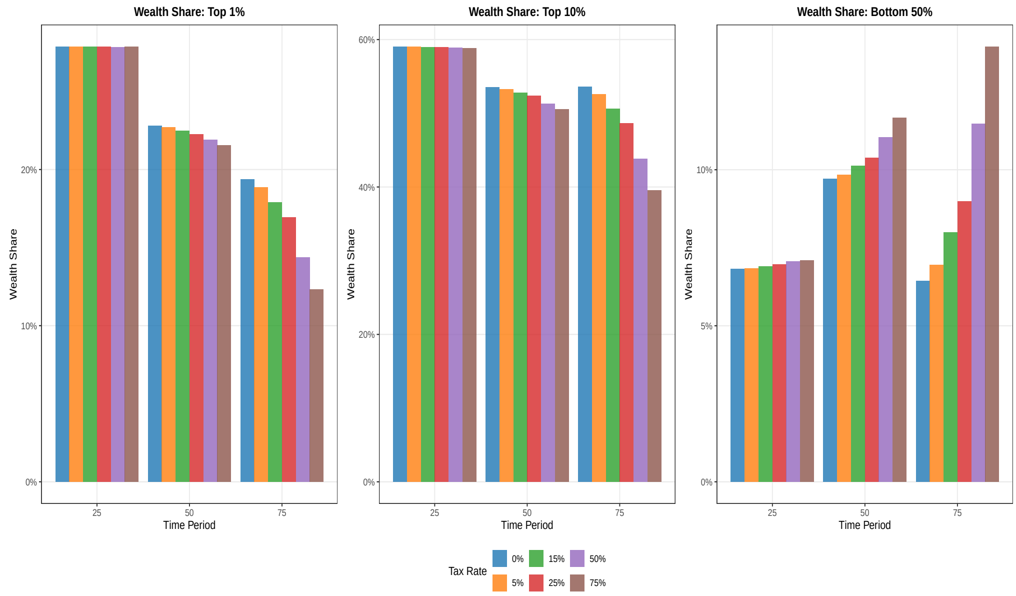



Figure 13: Consumption Share by percentiles across tax rates

## A.3 Wealth Shares across tax regimes by intervals




(a)




(b)

Figure 14: Wealth shares of households by percentile groups after every 25 years

# B Human Capital and Wealth Joint Initialisation

## B.1 Gini Based Method

We started the multigenerational simulation by jointly initialising human capital and wealth for the initial parent population. First, we want to assume that wealth is log-normally distributed to capture the skewness in the distribution of wealth, although the right tail of the empirical distribution of wealth is more skewed than using a log-normal distribution, which is often modelled in Pareto form (Benhabib & Bisin, 2018). Simplicity, we generate a log-normal to create an initial distribution; however, the wealth accumulation process will enable us to examine how the distribution of wealth will change over time, in intergenerational transmission.

To do so, we used the estimated annual median household wealth ($W_{50}$) of the total U.S. population and the estimated level of inequality in wealth, measured by the wealth gini ($G_W$). Since we assumed the initial distribution of wealth is log-normal, we then translate the estimated annual median wealth and the Gini for wealth into log-normal parameters from $G_W = 2\Phi(\frac{\sigma_W}{\sqrt{2}}) - 1$. By solving $G_W$ with respect to the standard deviation of the log-normal ($\sigma_W$), yield

$$\sigma_W = \sqrt{2}\Phi^{-1}\left(\frac{G_W + 1}{2}\right) \quad \text{and} \quad \mu_W = \ln(W_{50}) \tag{45}$$

where $\Phi$ is the standard normal cumulative distribution function; $G_W$ is the measure of the period Gini wealth inequality; $W_{50}$ is the median annual household wealth holding. This transformation allows us to convert the empirically estimated annual median and wealth inequality into log-normal parameters of $W_{i,1} \sim \ln(\mu_W, \sigma_W)$. This ensures that the initial distribution of wealth of the initial population will have exactly the targeted median wealth and standard deviation across individuals in the initial generation.

As evidenced in the Survey on Consumer Finance data (Bhutta et al., 2020; Jones & Neelakantan, 2023), there is a strong correlation between educational attainment and wealth; households with a higher level of education tend to be wealthier. We captured this empirical pattern by generating an initial distribution of wealth and educational attainment of the initial generation, such that there is some correlation between net worth and education determined by the parameter ($\rho$). However, for simplicity, we assumed the initial human capital (i.e. educational attainment) of the parent generation to be normally distributed and fixed across all time periods, which implies parents have a stock of human capital. Therefore, we used the Gaussian copula method to jointly generate initial human capital and wealth, which allows for generating a joint distribution while maintaining the marginals.

To achieve this, we let $W^0_{i,1} \sim N(0,1)$ and $h^0_{i,1} \sim N(0,1)$ be two independent normal distribution. We then define a correlated normal

$$h_{i,1} = \mu_{hc} + \sigma_{hc}(\rho W_{i,1} + \sqrt{(1-\rho^2)} \cdot h^0_{i,1}) \quad \text{and} \quad \ln W_{i,1} = \mu_W + \sigma_W W^0_{i,1} \tag{46}$$

Where $\mu_{hc}$ and $\sigma_{hc}$ are the estimated period mean and standard deviation of the years of schooling, and $\rho$ is the target Pearson correlation between wealth and educational attainment. We calibrate the empirically estimated value $\rho$ for the initial generation, reflecting substantial but not perfect correlation (wealthy families often have well-educated heads, though there are notable exceptions), and $\mu_W$ and $\sigma_W$ are the log-normal parameters of the transformation (see equation 45). Exponentiating gives the initial wealth distribution of the initial population

$$W_{i,1} = \exp(\ln W_{i,1}) \tag{47}$$

This generates a log-normal distribution of wealth with the desired median ($W_{50}$) and inequality in wealth given by Gini ($G_W$). This procedure yields a skewed wealth distribution, due to the high Gini inequality; a small fraction of individuals hold the majority of total wealth, as observed in reality in data.
However, since human capital is already in normal form, we round and truncate human capital such that schooling is between $[0, 24]$. Education years cannot be negative, and importantly, an individual cannot have more years of schooling than their current age. We enforce truncated such that $0 \leq h_{i,1} \leq (\text{a}_{i,1} - 6)$ and round $h_{i,1}$ to an integer. This means a 15-year-old parent individual can have at most 9 years of education, whereas an older parent (say 50 years old) could have the full $\sim 19$ years if drawn so. This step prevents inconsistencies (e.g. a teenager with a PhD). After truncation, we have each parent's initial human capital (education level) and wealth. By construction, wealth and education are positively correlated ($\rho$), so, for example, those with postgraduate education are likely to be among the wealthier, reflecting advantages of socioeconomic background. However, the correlation is far from perfect, allowing cases like a wealthy high-school dropout or an educated but asset-poor individual, which adds realism to the initial distributions.

### B.2 Percentile based method

Similarly, assuming log-normal distribution of wealth $W_{i,1} \sim N(\mu_w, \sigma_w^2)$. Using the empirical annual estimated median household wealth $W_{50}$ and the estimated top 10 annual wealth $W_{90}$. Additionally, given the standard normal CDF and quantile $\Phi^{-1}$, We let

$$W_{0.9} = \Phi^{-1}(0.9)$$

. Having obtained the median and top 10 annual wealth, we used these empirical estimates to derive the log-normal parameters of the initial wealth distribution, which are jointly distributed with human capital, using the same Gaussian copula method in the Gini-based initialisation (see equation 12).

Therefore, we take the median of a log-normal

$$\text{median}(W) = e^{\mu_w}$$

and then anchored the median target $W_{50}$, by setting

$$\mu_w = \ln(W_{50})$$

and the $90th$ percentile (top $10$) of the log-normal distribution, such that if

$$\ln(W) \sim N(\mu_w, \sigma_w)$$

then

$$\ln(W_{90}) = \mu_u + \sigma_w \cdot W_{0.9} \tag{48}$$

Therefore, by solving the deviation of the log-normal distribution, $\sigma_w$, we obtained

$$\sigma_w = \frac{\ln(W_{90}) - \ln(W_{50})}{W_{0.9}} \tag{49}$$

substituting for the mean of the log-normal distribution $\mu_w = \ln(W_{50})$ to obtain

$$\frac{\ln(W_{90}) - \ln(W_{50})}{\Phi^{-1}(0.9)} \tag{50}$$

Note that, to ensures our sample median wealth in the initial distribution of wealth produces a median exactly $W_{50}$, we used a centering technique from the drawn latent factor $W^0_{i,t} = N(0,1)$, to compute its median by using

$$W_{i,1} = W^0_{i,1} - \text{median}(W^0_{i,1}) \tag{51}$$

then

$$\ln(W) = \sigma_w + \sigma_w \cdot W_{i,1} \tag{52}$$

This yields a sample median of the initialised distribution exactly the targetted median ($W_{50}$), wealth and human capital are then computed, with correlation using the Gaussian copula as in the Gini-based method.

### B.3 Normalisation

To account for the overall wealth distribution, we standardise the effective wealth relative to the calibrated annual median wealth $W_{50}$, the process of initialising wealth for the initial generation at $t = 1$ and the initialised wealth distribution, $w_{i,1}$, by using $z_{i,t}$. Also, from the initialised wealth distribution, we compute the mean and standard deviation of the distribution, $\mu_{\ln w}$ and $\sigma_{\ln w}$, respectively, which is assume constant across the generations. Thus, the standardised effective wealth becomes:

$$z_{i,t} = \frac{\ln(1 + \tilde{w}^p_{i,t}/W_{50}) - \mu_{\ln w}}{\sigma_{\ln w}} \tag{53}$$

We calibrate per-year base progression probabilities from cumulative targets. For high school, the target cumulative completion rate by the end of $12$ years (from age $6$ to $18$) is $T_h$.

The implied per-year probability at the population means is $p_h = T_h^{1/12}$. Similarly, for post-secondary over 6 years (from age $19 - 24$) with cumulative target $T_{ph}$, we set $p_{ph} = T_{ph}^{1/6}$.

The log-odds of progressing one more year of schooling are given in equation 11

# C Calibration Details

## C.1 Mortality

After finding the value of the G-M slope in equation 38, we took the mortality life table estimates of the U.S., which provide the probability of death between age $a$ to $a+1$ for the entire age cohorts of the population. However, to consider only the death probabilities of the adult population, we choose anchor ages to reflect the mortality of the adult population in the U.S. The table 5 presents the extracted mortality life table of the adult population. Where $a_0$ and $a_1$

| $a_0$ | $q_{a_0}$ | $a_1$ | $q_{a_1}$ |
|---|---|---|---|
| 50–51 | 0.003 904 | 70–71 | 0.018 143 |
| 51–52 | 0.004 238 | 71–72 | 0.019 683 |
| 52–53 | 0.004 639 | 72–73 | 0.021 193 |
| 53–54 | 0.005 107 | 73–74 | 0.023 529 |
| 54–55 | 0.005 615 | 74–75 | 0.025 583 |

Table 5: U.S. CDC mortality life table of the adult population for 2019
Taken from Arias and Xu (2022)

are the range of the age window and $q_{a_0}$ and $q_{a_1}$ are their respective probabilities of dying from age $a$ to age $a+1$. These windows and their probabilities are used to calibrate the values for the Makeham term, $A$ and the magnitude of the Gompertz term, $B$. From the probabilities, we compute the integrated Hazard $H_a$ from the probability of dying from age $a$ to age $a+1$. In addition, instead of taking single-age anchors, we took the means of these window cohorts to reduce sampling noise and make the parameters more stable given by.

$$\bar{H}_{a0} = \frac{1}{5} \sum_{x=50}^{55} - \ln(1 - q_{a0}) \tag{54}$$

$$\bar{H}_{a1} = \frac{1}{5} \sum_{x=70}^{75} - \ln(1 - q_a 1) \tag{55}$$

The above formulation provides a safer way to work with probabilities and enables us to solve for $A$ and $B$ from a closed-form from the two age bands. From the discrete Gompertz-Makeham function in equation 4, we solve for the between-age $a$ and $a+1$ form these anchor ages to obtain a system of two equations 57.

$$H_{a_0}^{GM} = A + \frac{B}{C} \cdot (e^{C \cdot (a_0+1)} - e^{C \cdot a_0}) \tag{56}$$

$$H_{a_1}^{GM} = A + \frac{B}{C} \cdot (e^{C \cdot (a_1+1)} - e^{C \cdot a_1}) \tag{57}$$

Therefore, solving for the values of $A$ and $B$ from the discrete G-M function of the age window, $a_0$ and $a_1$, we obtain equations for the remaining Gompertz-Makeham parameters.

$$B = C \cdot \frac{H_{a_1} - H_{a_0}}{\Delta_1 - \Delta_0} \quad \text{and} \quad A = H_{a_0} - \frac{B}{C} \cdot \Delta_0 \tag{58}$$

Where $\Delta_0$ and $\Delta_1$ are given as

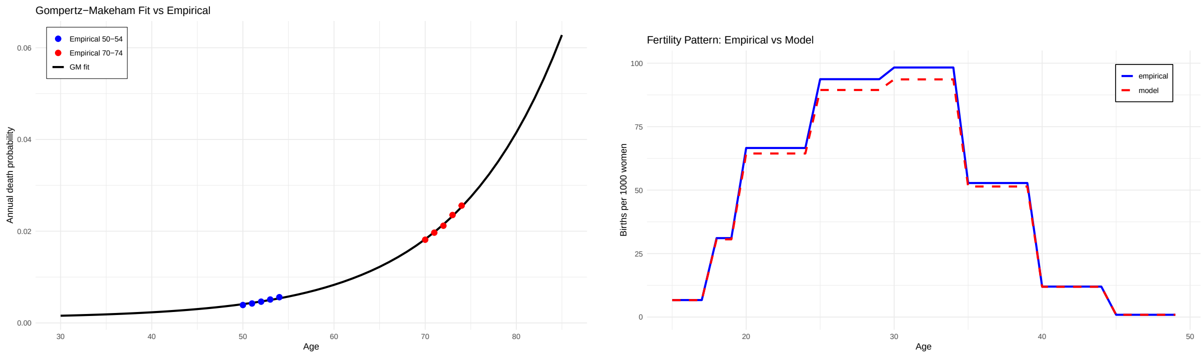
$$\Delta_0 = e^{C \cdot (a_0+1)} - e^{C \cdot a_0} \quad \text{and} \quad \Delta_1 = e^{C \cdot (a_1+1)} - e^{C \cdot a_1} \tag{59}$$

Thus, this method of obtaining the Gompertz-Makeham parameters from our discrete G-M function given in the demographic module and anchoring the mortality parameter to reflect adult mortality is both practical and well-grounded in the demographic literature. Additionally, fixing the slope $(C)$ based on doubling-time mortality using empirical data from U.S. life tables is a standard method that avoids the complexities of non-linear fitting, while still yielding realistic parameter values for our individual mortality computation to generate a realistic population dynamics, which is crucial in our understanding of intergenerational persistence.

### C.2 Age-Specific fertility

| Age cohort | ASFR(a) |
|---|---|
| 10 – 14 | 0.2 |
| 15 – 17 | 6.7 |
| 18 – 19 | 31.1 |
| 20 – 24 | 66.6 |
| 25 – 29 | 93.7 |
| 30 – 34 | 98.3 |
| 35 – 39 | 52.8 |
| 40 – 44 | 12.0 |
| 45 – 49 | 0.9 |

Table 6: Birth rate per 1000 women in each age-group in the U.S. for the year 2019 (Source: Osterman et al. (2025)




(a) (b)

Figure 15: (**a**): Values of $A$, $B$ and $C$ to fit the adult mortality life table CDC2019. (**b**): Conversion of CDC (2019) births per 1000 women into individual annual fertility probabilities used in the simulation. Both shows the relationship with respect to age, without shock

## C.3 Consumption and MPC

The tables below shows the empirical targets of the MPCs across the income and wealth distribution, their empirical basis and their implication for intergenerational transmission, with conservative targets.

| Household Type | Target mpy | Range | Empirical Basis |
|---|---|---|---|
| Poor | 0.55 | 0.50–0.60 | Liquidity constraints, immediate spending (Carroll et al., 2017; Jappelli & Pistaferri, 2014) |
| Median | 0.22 | 0.20–0.25 | Buffer-stock behaviour, moderate precaution (Carroll, 1997; Parker et al., 2013) |
| Wealthy | 0.15 | 0.12–0.18 | Permanent income, minimal transitory response (Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020) (Carroll et al., 2017) |

Table 7: Empirical Income MPC Targets by Household Type
*Note*: mpy = marginal propensity to consume out of income. Targets reflect annual consumption responses to income changes.

| Household Type | Target mpw | Range | Empirical Basis |
|---|---|---|---|
| Poor | 0.030 | 0.025–0.035 | Limited wealth effects, precautionary buffers (Carroll et al., 2011) |
| Median | 0.018 | 0.015–0.022 | Balanced decumulation, retirement drawdown (Mian, Rao, & Sufi, 2013) |
| Wealthy | 0.008 | 0.006–0.010 | Strong bequest motives, minimal decumulation (Carroll et al., 2017; Garbinti et al., 2022) |

Table 8: Empirical Wealth MPC Targets by Household Type
*Note*: mpw = marginal propensity to consume out of wealth. Targets reflect annual consumption responses to wealth changes, in dollars spent per dollar of wealth.

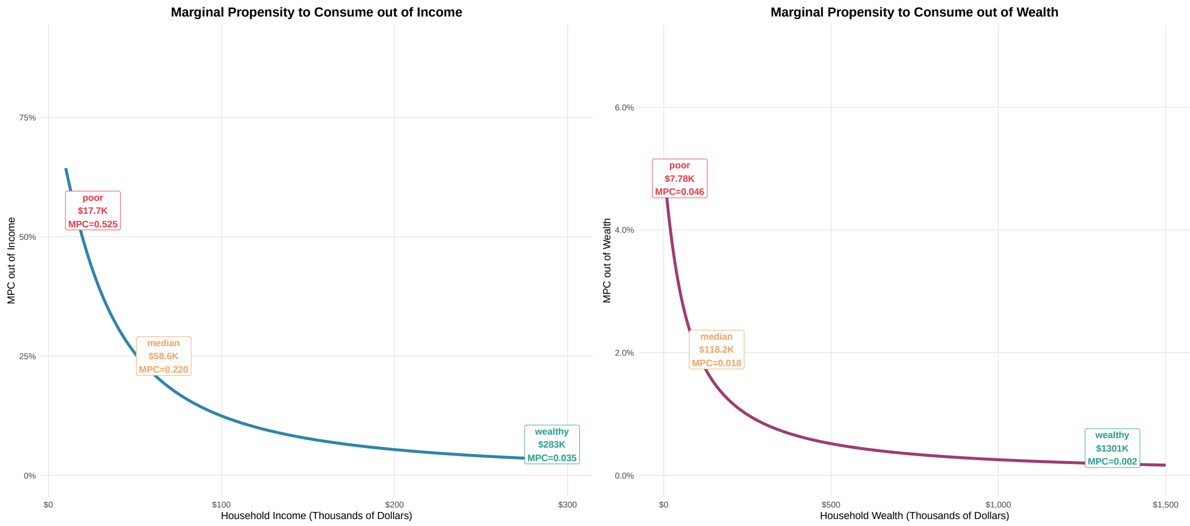



Figure 16: Calibration of $\alpha_y$, $\alpha_w$, $\gamma_y$ and $\gamma_w$ such that the marginal propensities match the target marginal propensities across the income and wealth percentiles using optimised elasticity parameters

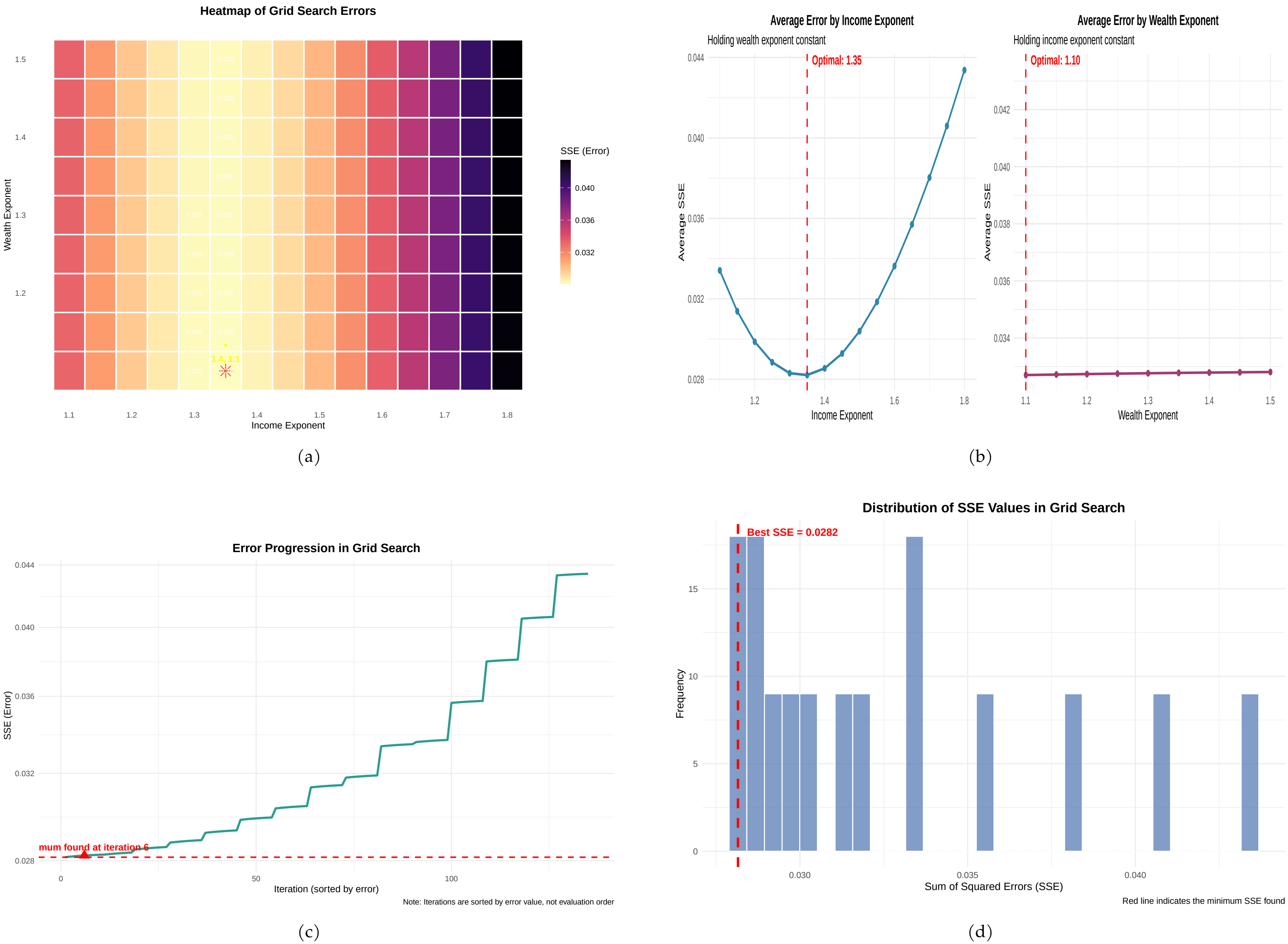



Figure 17: Figure (a) Combination of income and wealth exponent with the lowest error. Figure (b) The average error of each exponent of the MPC. Figure (c) Number of iterations that optimise errors. And Figure (d) The distribution of errors.

### C.4 The Mathematical Derivation of the Speed of Volatility ($\psi$)

As demonstrated earlier, as evidence to portfolio choice literature, as individuals transition to riskier assets, at the median wealth level, we computed the value of $\psi$ in equation 44 using this evidence of portfolio choice literature. By substitute equation (43) into equation (**??**):

$$\sigma^{vol}_{\min} + 0.5 \cdot (\sigma^{vol}_{\max} - \sigma^{vol}_{\min}) = \sigma^{vol}_{\min} + (\sigma^{vol}_{\max} - \sigma^{vol}_{\min}) \cdot \left[1 - (1 + W_{50})^{-\psi}\right] \tag{60}$$

Subtract $\sigma^{vol}_{\min}$ from both sides:

$$0.5 \cdot (\sigma^{vol}_{\max} - \sigma^{vol}_{\min}) = (\sigma^{vol}_{\max} - \sigma^{vol}_{\min}) \cdot \left[1 - (1 + W_{50})^{-\psi}\right] \tag{61}$$

Divide both sides by $(\sigma^{vol}_{\max} - \sigma^{vol}_{\min})$ (assuming $\sigma^{vol}_{\max} \neq \sigma^{vol}_{\min}$):

$$0.5 = 1 - (1 + W_{50})^{-\psi} \tag{62}$$

Rearrange equation (62) to solve for $\psi$

$$(1 + W_{50})^{-\psi} = 0.5 \tag{63}$$

Take the natural logarithm of both sides:

$$-\psi \cdot \ln(1 + W_{50}) = \ln(0.5) \tag{64}$$

Note that $\ln(0.5) = -\ln(2)$:

$$-\psi \cdot \ln(1 + W_{50}) = -\ln(2) \tag{65}$$

Multiply both sides by $-1$:

$$\psi \cdot \ln(1 + W_{50}) = \ln(2) \tag{66}$$

Solve for $\psi$:

$$\boxed{\psi = \frac{\ln(2)}{\ln(1 + W_{50})}} \tag{67}$$

### C.5 Return Shock

Additionally, the t-distribution random shock $\eta_{i,t}$ (in equation 22) with $\nu$ degrees of freedom is scaled to unitary such that the return shocks are exactly the volatility shocks. The t-distribution allows us to introduce heavy-tail shocks often observed in financial assets, due to high frequency or extreme positive or negative events in financial assets, which dominate the portfolios of the wealthy. As Connolly, Haeck, Laliberté, et al. (2020) documented stylised facts on some properties of asset returns, such as heavy-tail, gain/loss asymmetry, etc. Incorporating a t-distribution shock will allow us to model periods of favourable and non-favourable financial shocks which drive wealth accumulation, especially positive financial shocks on risky assets.

Therefore, the return shock on wealth is given as:

$$\eta_{i,t} = \sigma \cdot t_{\nu} \tag{68}$$

Where $\sigma$ is the annual independent shock, which is set to unit variance (i.e. $\sigma = 1$), such that the wealth shock is the wealth-dependent volatility shock. The t-distribution is scaled to allow shocks to be a volatility shock by

$$\bar{\nu}_{i,t} = \sqrt{\frac{\upsilon}{\upsilon - 2}} \quad \text{such that} \quad \eta_{i,t}^{\text{scaled}} = \frac{\eta_{i,t}}{\nu_{i,t}} \tag{69}$$

Since the standard $t_{\nu}$ distribution degree of freedom $(\nu)$ has $\mu_{\upsilon} = 0$ and $\sigma_{\upsilon}^2 = \frac{\nu}{\nu - 2}$ for $\nu > 2$. This scaling ensures that we achieve unit variance, and the shock is the volatility shock.

This scaling is crucial for correct calibration. The degree of freedom $(\nu)$ is then fine-tuned to match empirical data on the kurtosis of asset returns; a smaller $\nu$ results in heavier tails, increasing the probability of extreme return events that are a key mechanism for wealth concentration (Benhabib & Bisin, 2018). The $\nu$ is not directly observed, but it can be computed from the excess kurtosis, which is often estimated (Bollerslev, 1987; Cont, 2001). However, it's often estimated for minutes or daily frequencies. Cont (2001) estimated the minute return of S&P500 with a kurtosis $(K)$ of $15.95$, and the excess kurtosis $(EK)$ can be obtained from the kurtosis by $EK = K - 3$ which gives an $EK = 12.95$. Moreover, the degree of freedom $(\nu)$ is also obtain from the $EK$ by solving

$$\nu = 4 + \frac{6}{EK} \approx 4.46$$

. Given financial returns are extremely fat-tailed at high frequency, we set a conservative value for $\nu$, which is appropriate for capturing the tail of annual returns and represents a significant reduction from the ultra-high kurtosis obtained at 5-minute frequencies.

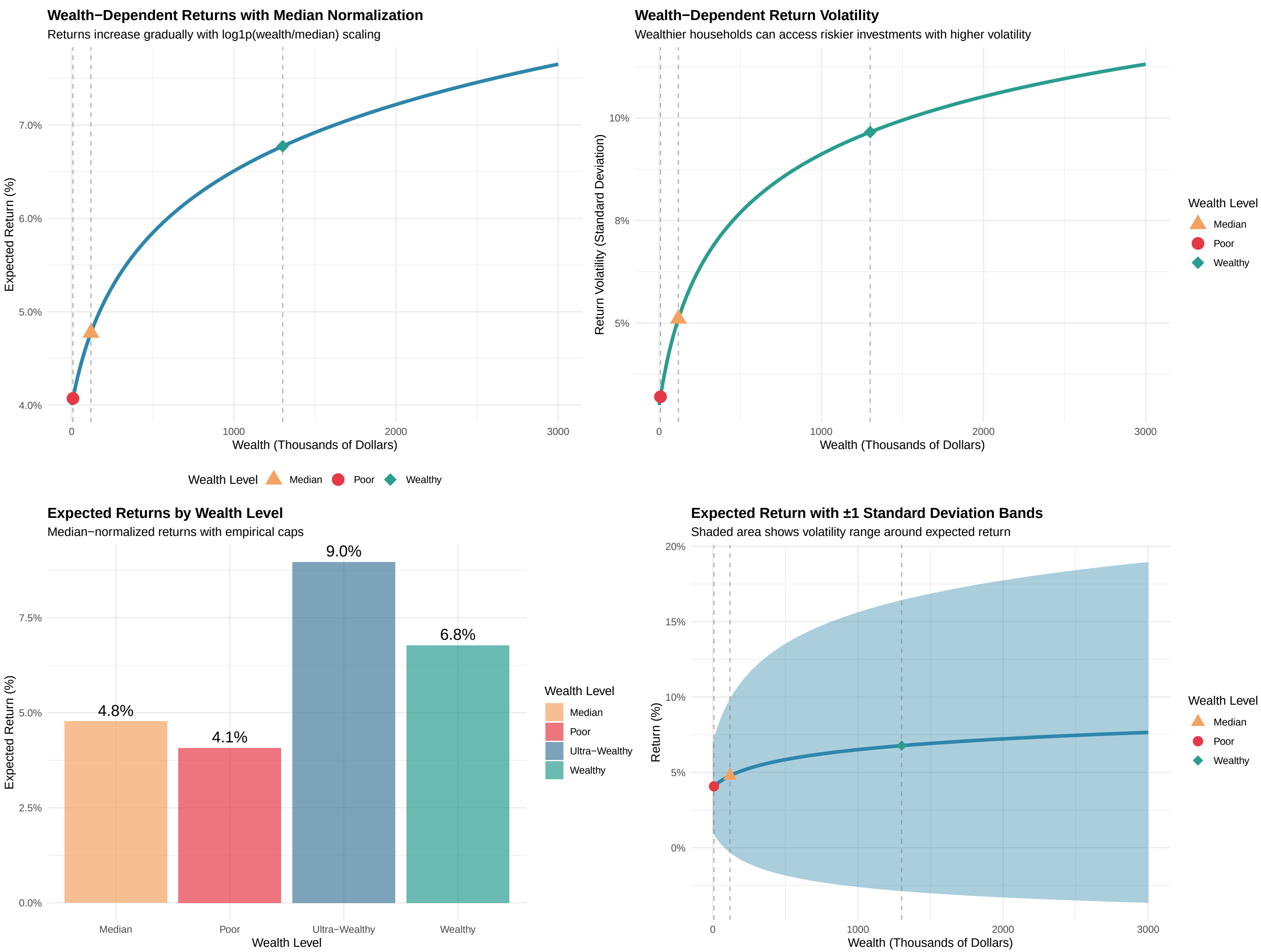



Figure 18: Top left: Shows that return increases with wealth. Top right: Volatility also increases with wealth. Bottom left: The 2% target return difference between the median and top 10 is met. Bottom right: Expected return ± one standard deviation (volatility) bands; band width increases with wealth because volatility itself grows with wealth.
Note: These results are after normalising individual wealth relative to the median wealth, with no shock.

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