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Fertility and Education Decisions in Developing Countries: The Role of Social Norms[*]

Trang Le[†] George Kudrna[‡] John Piggott[§]

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Abstract

This paper studies how the social norm of intergenerational support, where parents anticipate financial assistance from their adult children in old age, influences fertility and education investment decisions in developing countries. We develop a dynamic life-cycle model with uncertain labor income and endogenous fertility and education choices, incorporating expectations of private transfers driven by this norm. Using data from the Indonesian Family Life Survey, we estimate labor income profiles and income risks, account for parental financial constraints, and document the prevalence of intergenerational transfers in the 2000s. The model is calibrated to match key empirical patterns in fertility and schooling. Counterfactual simulations reveal that a weakening of this social norm leads to declines in both fertility and educational investment, particularly among lower-educated parents. Our findings underscore the central role of intergenerational transfers in shaping demographic and human capital outcomes and provide new insights into the persistence of educational inequality in developing economies.

JEL Classification: J13, J24, J62, D15

Keywords: Fertility, Human capital, Education investment, Intergenerational transfers, Life-cycle model.

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1 Introduction

This paper investigates the impact of the social norm of intergenerational support on parents' decisions regarding fertility and educational investments in developing countries. Historically, the expectation that adult children provide financial assistance to their aging parents has significantly influenced family planning and education choices, particularly in East and Southeast Asia. However, evidence suggests that this norm is weakening, with potentially important implications for demographic behavior and long-term economic outcomes (Ogawa and Retherford, 1994).[1]

An extensive literature, focused on a developed-country context, links fertility and education decisions through the well-established quantity-quality trade-off framework of Barro and Becker (1989). This theory explains why poorer parents often have more children with lower educational investment in each child (De La Croix and Doepke, 2003), while wealthier families invest more intensively in fewer children (Becker et al., 2018). However, these frameworks often overlook the unique role of informal social support structures and norms in shaping decisions in less developed settings.

In developing economies, where formal social protection for old age is limited, children serve both as a source of utility (or emotional value) and as a form of financial insurance. Thus, fertility and education decisions are shaped not only by quantity-quality trade-offs driven by parental altruism but also by expectations of future financial transfers from children.

Intergenerational transfers have been shown to influence fertility, saving and education investment decisions (Cox and Jimenez, 1990; Cigno, 1993; Deaton, 1998; Oliveira, 2016) and a growing body of research has highlighted the role of old age support norms in determining parental behavior (Cai et al., 2006; Curtis et al., 2015; Bau, 2021; Choukhmane et al., 2023). Yet much of this literature focuses on China, where fertility behavior has also been shaped by the one-child policy – a strong exogenous constraint (Banerjee et al., 2014). This focus

[1] Ogawa and Retherford (1994) find that while the norms of filial responsibility for elderly parents in Japan remained relatively stable between 1963 and 1986, they weakened significantly during the 1990s.

limits the applicability of existing findings to other developing countries, where fertility choices are less constrained by policy, but still influenced by changing social expectations.

Our study addresses this gap by examining how evolving norms of intergenerational support influence fertility and education investment decisions in a representative developing country context. In doing so, it also considers broader implications for inequality among the elderly and intergenerational mobility.

To capture these dynamics, we develop a structural life cycle model in which parents make fertility and education investment choices while facing uncertain labor income and financial constraints. Crucially, our model incorporates expectations of future intergenerational transfers based on the prevailing filial norms. Individuals in our model choose to have children not only because they derive utility from them, but also because they expect children to provide financial support in old age. Thus, children are treated as both a normal good and an investment asset.

We use Indonesia as a representative case. Drawing on rich panel data from the Indonesia Family Life Survey (IFLS), we document several key features of the economy – including significant earnings gaps by education level, distinct fertility and education investment patterns, and prevalent intergenerational transfers – that both motivate our analysis and serve as input for calibrating the model.[2]

The model is calibrated to match observed empirical patterns and is used to simulate counterfactual scenarios in which the strength of filial norms varies. The results reveal that stronger expectations of old-age support increase fertility and raise overall education investment, though the magnitude and direction of responses differ across household types. Fertility increases most among high-educated and wealthier parents, who are better positioned to take advantage of the higher expected returns from intergenerational transfers. In contrast, the most substantial gains in education investment occur among low-educated and lower-income households, for whom stronger norms heighten the perceived value of children's future earnings. Conversely, weakening expectations of intergenerational support,

[2] The IFLS is a comprehensive socio-economic survey that provides detailed information on a wide range of economic outcomes, including behaviors of households (as documented in Strauss et al., 2016). We used data from three IFLS waves conducted in 2000, 2007 and 2014.

which is increasingly observed in many developing countries that undergo rapid social and institutional change, leads to declines in both fertility and education investment. The fertility decline is more pronounced among high-educated households, while the drop in education investment is disproportionately larger among low-educated households, who face tighter financial constraints and lack alternative sources of old-age security. These shifts amplify disparities in educational attainment, deepen old-age consumption inequality, and reduce intergenerational mobility.

These findings underscore the importance of intergenerational norms in explaining persistent inequality and demographic trends in developing economies. They also highlight the urgency of policy interventions – particularly those that expand access to education and strengthen social protection for the elderly – to buffer the effects of eroding family support systems.

This paper brings together several strands of literature into a unified modelling framework. First, it builds on work examining the relationship between fertility and human capital decisions. It extends the classical quantity-quality trade-off proposed by Barro and Becker (1989) and the human capital investment theory of Becker (1964) by incorporating the role of intergenerational support expectations within a dynamic framework, as in Curtis et al. (2015) and Hsu and Le (2024).[3] Our model adds to this literature by jointly modeling fertility and education decisions, under financial frictions and incomplete markets, as emphasized in Altig and Davis (1993), Keane and Wolpin (2001), Fernandes (2012), Miyazaki (2016) and Abbott (2022).

Second, we contribute to the growing literature on how evolving social norms shape economic behavior. Extensive empirical evidence consistently shows that informal old-age support remains crucial in developing countries. For example, Cox and Jimenez (1990) documents the prevalence of private transfers across countries, while İmrohoroğlu and Zhao (2018) and Pei and Cong (2020) show the continued reliance on family support in China. Cai et al. (2006) emphasizes the insurance role of transfers in settings with limited pensions. Recent work has started to formally model these norms within dynamic

[3] Both Curtis et al. (2015) and Hsu and Le (2024) focus on fertility choices, abstracting from education investment.

frameworks, including Curtis et al. (2015), Bau (2021) and Choukhmane et al. (2023). Our study complements this literature by applying this framework to a country not subject to strict fertility regulations, thus expanding the external validity of these models.

Third, we address the gaps in the literature on intergenerational mobility in developing countries. Although foundational models such as Becker and Tomes (1979) and extensions such as Solon (2004) are widely applied in developed country contexts, the dynamics of mobility under financial constraints and limited public services are less well understood. Our approach builds on the tradition of structural life-cycle modeling, particularly Daruich and Kozlowski (2020), and incorporates the social norm of support for old age and a specification of a direct altruistic utility function for educational investment, as in De La Croix and Doepke (2003). By embedding these elements within a model calibrated to Indonesia, we provide new insights into how evolving social norms shape mobility patterns in lower-income country settings.

Finally, this paper contributes methodologically to the literature on estimating income risks in developing countries. Using rich IFLS data, we construct detailed earnings profiles with stochastic components, capturing heterogeneity in income volatility across education levels. This extends the approaches developed by Karahan and Ozkan (2013) and Blundell et al. (2008), which have been applied largely in developed economies. Our estimation accounts for the distinct challenges of informal and agricultural labor markets. On the computational side, we implement an endogenous grid method (EGM) for discrete-continuous choice problems following Iskhakov et al. (2017), Carroll (2006), and Fella (2014), allowing for a more realistic representation of household decision-making about fertility and education investment.

The remainder of the paper is structured as follows. Section 2 presents key empirical facts on income, fertility, education investment, and intergenerational transfers by parental education level in Indonesia, which inform the model's calibration. Section 3 introduces the structural life-cycle model, outlining the economic environment and agents' decision problems, while the estimation approach and the parameterized benchmark economy are presented in Section 4. Section 5 reports the main quantitative results from counterfactual simulations, analyzing how changes in filial norms affect fertility, education investment, inequality in old age, and intergenerational mobility. Section 6 examines how education cost shapes household responses to changing intergenerational support norms. Section 7 summarizes the main findings and discusses policy implications.[4]

2 Empirical Analysis

This section is motivated by several stylized facts characteristic of developing countries, using Indonesia as a representative example. As one of the largest low- and middle-income countries, Indonesia shares many characteristics with other developing economies, including earnings inequality, educational stratification, high dependence on informal support systems, and limited old age security.

2.1 Data Selection

The primary data source for empirical analysis is the Indonesia Family Life Survey (IFLS), covering the period 2000 to 2014.[5] We closely follow the data construction and sampling strategy in Kudrna et al. (2020) and Kudrna et al. (2022), with minor adjustments to ensure consistency with the life cycle model developed in the next section. In particular, for the estimation of earnings profiles, the following restrictions are applied:

- The age range is restricted to 25-60, capturing the core working years from post-education entry to retirement.
- Only male workers are included, as female labor force participation tends to be lower and more irregular (owing to part-time work or caregiving), a standard practice in the literature (see, e.g., Jones and Tertilt, 2006).
- Individuals with zero income – including the unemployed and unpaid family workers – are excluded.

[4] This paper is accompanied by several appendices that provide further details on model solution methods, earnings process estimation, and additional results.
[5] IFLS data are available at http://www.rand.org/labor/FLS/IFLS.html, with documentation published by Strauss et al. (2016).

- Labor earnings for wage workers are calculated as the sum of reported salaries and bonuses from all wage jobs. For self-employed individuals (in both farm and non-farm sectors), income is proxied by reported net profits.
- Educational attainment is classified into two groups: low-educated (not completing high school) and high-educated (high school graduates and above).

To examine fertility choices, education investment, and intergenerational transfers, we only use males who are household heads or spouses, representing household characteristics. The analysis is restricted to cohorts born between 1955 and 1974, who are old enough to have made both fertility and education investment decisions and to have supported elderly parents financially.

The remainder of the section presents descriptive evidence on four empirical patterns: lifecycle labor earnings between education groups, fertility differentials, parental investment in children's education, and the role of private intergenerational transfers. These patterns motivate the structure and calibration of our model.[6]

2.2 Labor Earnings over the Life Cycle

Figure 1 presents age-earnings profiles by education level using IFLS data, revealing two notable patterns. First, as is common in many labor markets, individuals with higher education earn significantly more than their low-educated counterparts. Second, the earnings profile for the high-educated group is noticeably steeper, indicating faster income growth over the life cycle compared to the low-educated group. This pattern is consistent with the notion that education enhances productivity and earnings potential over time.

While these raw profiles may reflect both year and cohort effects – since the data pool spans 2000 to 2014 – our estimation strategy controls for these confounding factors. Even after accounting for such effects, the earnings differential between high- and low-educated individuals remains economically significant.[7]

[6] In addition to our own analysis, several stylized facts discussed here are also reflected in Kudrna et al. (2023).
[7] See Section 3 and Appendix A.2 for details on the earnings estimation methodology.

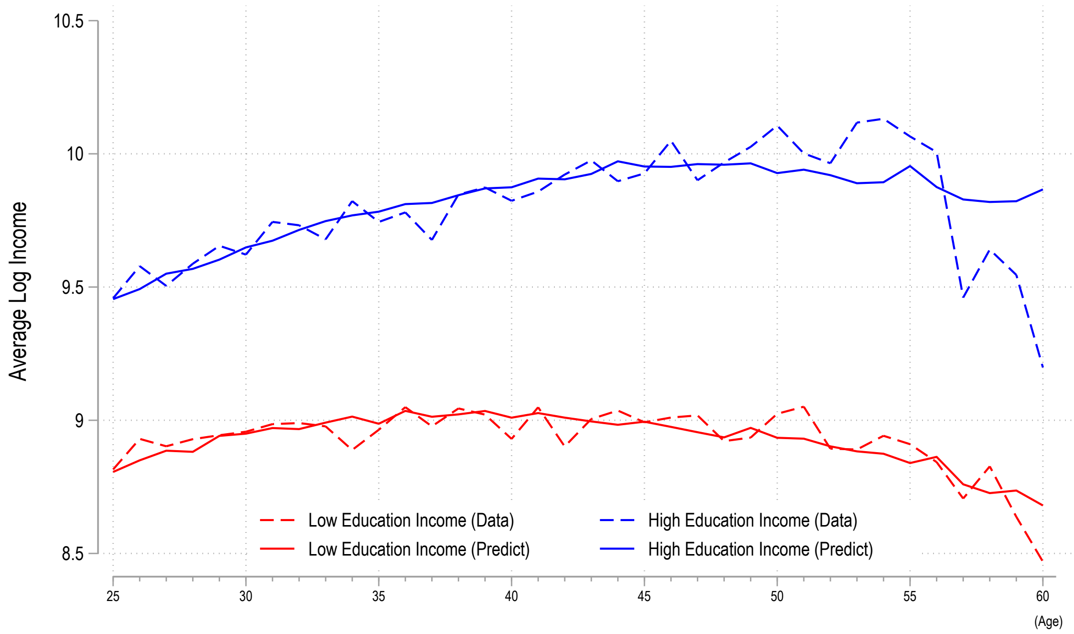


FIGURE 1: Earnings Profiles by Education

Note: The figure displays mean annual real labor earnings by age for men aged 25–60 using IFLS 2000-2014. Wage earnings aggregate salary and bonuses across jobs; self-employment earnings are proxied by reported net profits. Observations with zero income are excluded. "Predicted" series are fitted values from a Mincer-type specification as detailed in Section 3 and Appendix A.2.

2.3 Fertility Differentials

This subsection examines fertility differentials across education and income groups using IFLS data. In the literature, fertility behavior is often linked to how parents perceive children – either as a source of direct utility (a normal good) or as an investment in future returns. If parents derive utility from simply having children, we expect a positive relationship between fertility and income. Conversely, if parents value their children well-being (altruism motive) and/or support they receive in old age (investment motive), a negative relationship between fertility and income is expected to arise.

We aim to empirically assess how these motives manifest in household fertility behavior. Fertility is measured at the household level, based on the number of surviving children reported by women in the IFLS. These reports are then linked to their spouses, as father's education and status are used as the representative household characteristics in our analysis.[8]

Table 1 displays the average number of children by father's educational attainment. High-educated fathers have, on average, 2.6 children, compared to 2.9 children among low-educated fathers. This negative gradient between education and fertility mirrors patterns observed in both high- and low-income countries, and aligns with existing theoretical models that emphasize either the cost of raising children or the returns to investing in child quality.[9]

TABLE 1: Fertility by Education

Education Type	Fertility Rate
Low-educated Household	2.9
High-educated Household	2.6

Note: Fertility is measured as the number of alive children for specific cohorts using IFLS 2014. The father's education is used as the representative of the household.

Table 2 further explores the relationship between fertility and income quintiles, showing a clear negative gradient. Households in the lowest income quintile report an average of 3.5 children, while those in the highest quintile report 2.5. This inverse relationship between income and fertility is consistent with findings in the existing literature (e.g., Jones and Tertilt (2006)) and aligns with national-level evidence from the 2012 Indonesia Demographic and Health Survey (IDHS).[10]

2.4 Education Investment

This subsection presents descriptive evidence on intergenerational education investment, focusing on households where both father and child educational attainment can be

[8] The total fertility rate is also used to measure fertility as commonly used in the literature, and following Daruich and Kozlowski (2020), we restrict the sample to women who are household heads or spouses of household heads, of childbearing age of 15 to 49, and reported as married.

[9] It is worth noting that when education is categorized into three levels – high school dropout (Low), high school graduate (Middle), and beyond high school (High) – the fertility gap is mainly between the Low and Middle groups, with little difference between Middle and High.

[10] The IDHS analysis also shows a clear negative relationship between household wealth and fertility, and this pattern holds consistently across birth cohorts.

Table 2: Fertility by Income

Income Quintile	Fertility Rate
Lowest	3.5
Second	3.1
Middle	2.8
Fourth	2.7
Highest	2.5

Note: Fertility is measured as the number of alive children for specific cohorts using IFLS 2014.

observed. Using IFLS 2014 data, we select fathers who are household heads or spouses of household heads and link them to their children, whether coresident or non-coresident. To ensure that educational attainment is largely complete, we restrict the children's age to 18 and above. This yields a sample of 7209 father–child pairs, of which 66% of fathers are classified as low-educated and 34% as high-educated.

Table 3: Child Education by Father's Education

	Father's Education	
Child's Education	Low-educated	High-educated
Share of Low-educated Children	0.47	0.06
Share of High-educated Children	0.53	0.94

Note: A child/father is classified as high-educated if they completed high school or more; otherwise they are low-educated. Father's education determines the household classification.

Table 3 presents the breakdown of children's education by father's education level. Among children with low-educated fathers, only 53% attain a high school education or higher, while 94% of children with high-educated fathers reach this level. This stark contrast illustrates a strong intergenerational correlation in educational attainment, suggesting persistent educational inequality across generations.[11]

[11] Note that the cohorts used in this analysis are unaffected by Indonesia's senior high school compulsory policy implemented in 2021.

2.5 Private Transfers

This subsection examines private monetary transfers from adult children to their elderly parents, highlighting their importance – especially among low-educated households – as a source of old-age support.

Using IFLS data from 2000 to 2014, we focus on adult children born between 1955 and 1974, linking them to their elderly parents. This yields a sample of 4,717 child-parent pairs. Transfer data are drawn from IFLS survey questions tk26a1 and tk26a2, capturing both upward (child-to-parent) and downward (parent-to-child) financial flows. The analysis is restricted to non-coresident children, as transfers within the household are difficult to disentangle in purpose and value.[12] Average net transfers are calculated over the observed life cycle, including households that report zero transfers. Transfers related to major life events – such as tuition payments or housing assistance – are excluded to focus on regular financial flows.

Figure 2 presents the composition of income sources for the elderly aged 60 and above, categorized into four types: labor income, non-labor income, asset income, and private transfers from children.[13] The data show that labor income and private transfers jointly account for the majority of total income among older individuals – each contributing more than 40% on average. In contrast, asset and non-labor income sources (e.g., pensions) remain minimal. For example, in 2000, only 3.9% of the elderly reported asset income, rising modestly to 4.9% by 2014. This persistent pattern underscores the continued reliance on intergenerational financial support in old age.[14]

[12] Transfers from co-residing children are excluded due to limited visibility on their amount and motivation.

[13] For a detailed breakdown of income source construction, see Kudrna et al. (2022).

[14] Similar findings for old-age income composition in Indonesia and other Southeast Asian countries are provided by World Bank (2016).

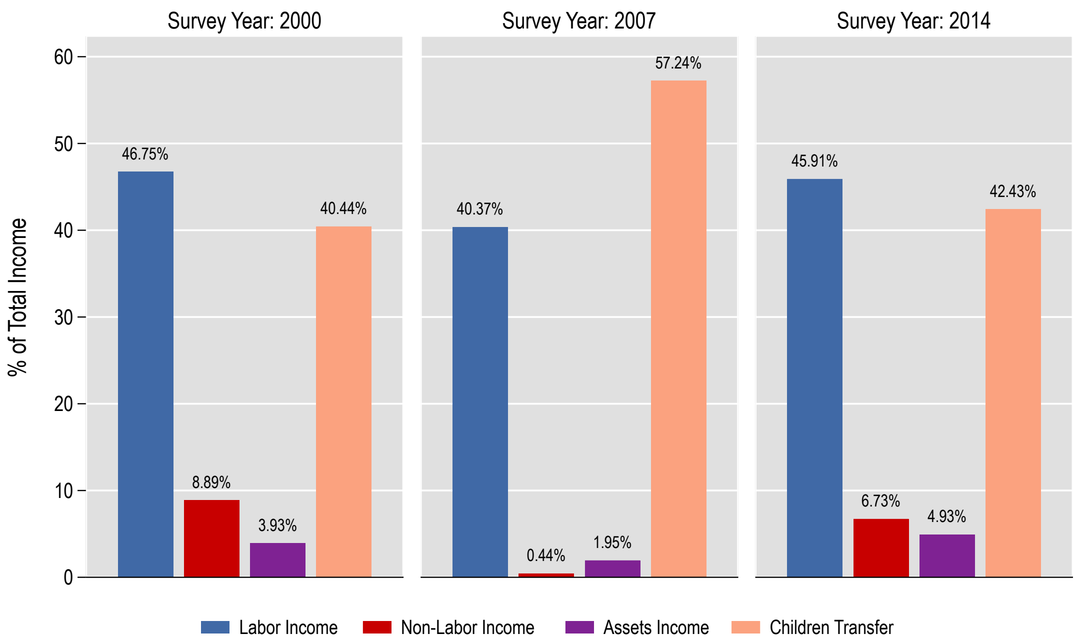


FIGURE 2: Income Sources of Older People over Time

This figure presents shares of total income from labor, non-labor, asset income, and net child-to-parent transfers for parents aged 60+. Source: IFLS 2000-2014, authors' calculation

Despite the central role of private transfers, total income for the elderly remains well below the average earnings of working-age males. As shown in Kudrna et al. (2022), income replacement rates drop dramatically with age – from 33.4% for those aged 50-59 to just 16.6% for those 70 and older. This suggests that while intergenerational support is common, it only partially offsets income loss in retirement and may reflect relatively weak enforcement or coverage of social norms.

The significance of private transfers also varies by parental education. Figure 3 illustrates income composition by educational level. Among the low-educated elderly, both labor income and private transfers are the dominant sources (45% and 48.6% of their total income). In contrast, high-educated elderly derive 33.1% of income from labor and 28% from child transfers. For this group, non-labor income (including pensions and savings) plays a larger role. These patterns confirm that private transfers are a more critical financial pillar for the less educated elderly, who tend to lack formal savings and pension coverage.

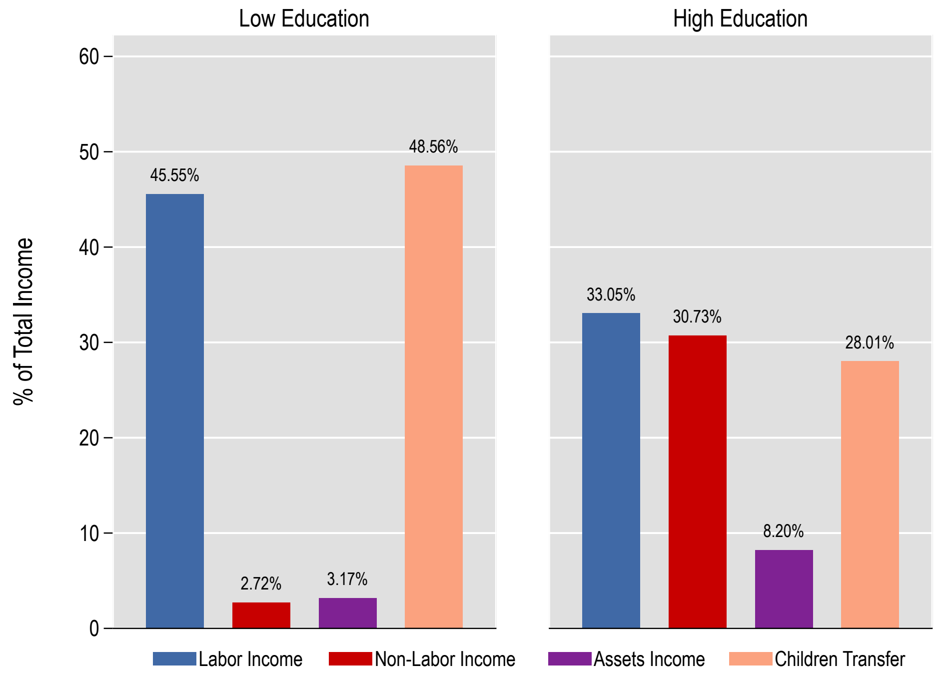


FIGURE 3: Income Sources of Older People by Education

Note: This figure presents shares of total income from labor, non-labor, asset income, and net child-to-parent transfers for parents aged 60+ by education types of the parents. Source: IFLS 2000-2014, authors' calculation

In summary, the evidence from Indonesia confirms that private financial transfers from children serve as a key support mechanism for aging parents, especially those with low educational attainment. This intergenerational dynamic motivates the inclusion of old-age support norms in the life-cycle model described and estimated in the next two sections.

3 Model

This section presents a life-cycle model developed to analyze how social norms of intergenerational support influence fertility and education investment decisions in developing countries. The model builds on the classical quantity-quality trade-off literature initiated by Barro and Becker (1989), where parents weigh the number of children (fertility) against the quality (education) of each child, under the assumption of altruistic motives.[15] A

[15] As in most of the literature, the model assumes a generic parent and does not consider marriage or gender differences in parental input.

central innovation is the introduction of an institutional norm – monetary transfers from adult children to their elderly parents – as a key channel determining parental behavior. This feature is particularly prominent in settings such as Indonesia, where public pensions are limited and children function as both consumption goods and financial assets in old age.

Consistent with the empirical motivation presented in the previous section, this model incorporates expectations of old-age support into the parental decision problem. Parents anticipate receiving a fixed share of each child's income, which they can influence indirectly by choosing how many children to have and whether to invest in their education. This link transforms traditional quantity-quality trade-offs into a broader investment problem shaped by informal institutions.[16]

In the following, we first describe the demographic structure and life-cycle stages faced by individuals. We then detail preferences, child-rearing and education costs, the norm and intergenerational transfers, and the dynamic decision problems faced by agents in different life phases.

3.1 Demographic Structure and Lifecycle Stages

The model is defined in discrete time, where each period represents one year. Let $j \in \{0, 1, \ldots, J\}$ denote an individual's age. The first model period, $j = 0$, corresponds to age 18, and the final period $j = J^d$ to age 90. Individuals survive from age j to $j + 1$ with age-dependent survival probability ρ_j.

Agents pass through four life-cycle stages: (i) working, (ii) fertility, (iii) education investment in children, and (iv) old age (only where $\rho_j < 1$). These are illustrated in Figure 4 for the generation $G = 1$ of parents. Prior to age J_w, individuals are economically inactive dependents (depicted by the generation $G = 2$ of children) whose consumption is determined by their parents.

[16] Recent life-cycle models have included social norm-driven transfers, particularly in the Chinese context (e.g., Choukhmane et al., 2023). Our contribution is to embed this channel in a richer setting with income uncertainty and credit constraints, and to apply it to Indonesia where fertility has not been regulated and private transfers remain widespread.

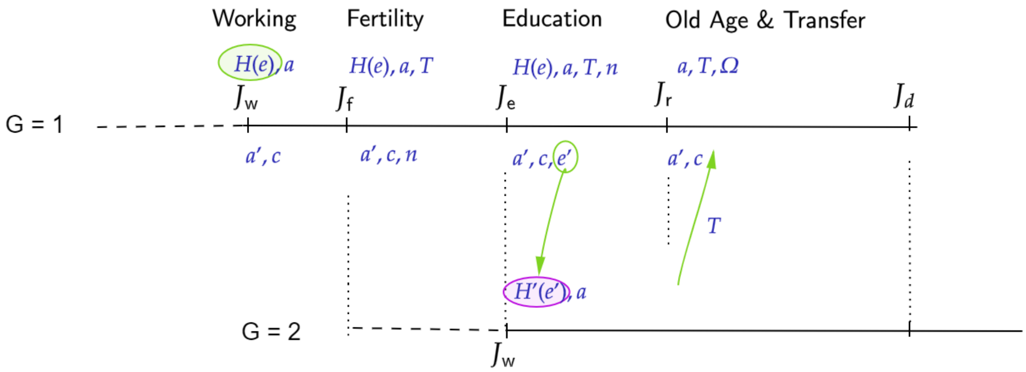


FIGURE 4: Lifecycle Stages and Decisions

At age J_w, individuals become economically active. Their educational attainment – low (less than high school) or high (high school graduate) – is fixed at this stage and determines their effective labor input. Labor income is subject to age- and education-dependent stochastic productivity shocks. Individuals supply labor inelastically and decide each period how much to consume and save.

At age J_f, they decide on fertility, choosing the number of children n as a discrete choice.[17] Altruistic parents derive utility from having children, but raising them incurs both time and monetary costs. Parents pay for those two costs until their children become independent.

Beginning at age J_e, individuals decide whether to invest in their children's education. This is a binary choice – high versus low education – that affects children's future earnings and, in turn, the financial support they provide to parents in old age. Thus, education investment is motivated both by altruism and by expected returns through intergenerational transfers.

After children become independent, individuals enter the old-age stage when they face falling survival probabilities ρ_j. They retire and finance consumption from savings and transfers received from their adult children. Individuals live to a maximum age J_d (with $\rho_{J^d} = 0$).

[17] The discrete fertility choice is both empirically realistic and allows for modeling childlessness.

3.2 Endowment

At the point of economic independence (age J_w), individuals are endowed with two initial state variables: their educational attainment (e) and their asset holdings (a). Education can be either low (not completing high school) or high (completing high school), and this discrete educational type determines the skill level of individuals in the labor market.

While working, an individual's effective labor is determined by both age and education level. Earnings are the product of effective labor and a stochastic income shock, which is also allowed to vary by educational group. In particular, the income process includes idiosyncratic shocks that are education-dependent, reflecting differences in earnings volatility across skill levels.[18]

3.3 Preferences

Individuals derive utility from consumption (c), the number of children (n), and their children education (e). When individuals are childless, utility depends only on consumption and follows a standard CRRA specification:

Individuals have preferences over the choice variables, i.e., consumption (c), number of children (n), and children's education (e). When living without children, an individual's preference over consumption follows the CRRA utility function:

$$U_j(c) = \frac{c^{1-\mu}}{1-\mu}, \tag{1}$$

where μ is the coefficient of relative risk aversion and β is the subjective discount factor.

Parents are altruistic toward their children in two dimensions: they value the number of children they have, and they care about their children's future well-being. Altruism toward child quantity is captured by:

$$v(n) = \lambda_n \log(1+n), \tag{2}$$

[18] The estimation of earnings profiles and income dynamics by education type is described in the next section.

where λ_n governs the strength of fertility preference and $v(n) = 0$ if $n = 0$.

From the education stage onward, parents also derive utility from the expected net income of their children, representing the combination of altruistic concern and an investment motive. This is captured by a warm-glow utility term, weighted by a function $g(n)$ that increases concavely with n. The utility depends on the log of expected net income received from each child, denoted I'. This is captured by a warm-glow utility term, weighted by a function $g(n)$ that increases concavely with n. The utility depends on the log of expected net income received from each child, denoted I'.[19]

To summarize, preferences over consumption, children, and education can be written as follows:

$$\frac{c^{1-\mu}}{1-\mu} + v(n) \quad \text{for } j \in \{J^f, \ldots, J^e - 1\}, \tag{3}$$

$$\frac{c^{1-\mu}}{1-\mu} + v(n) + g(n)u(I') \quad \text{for } j = J^e, \tag{4}$$

where the investment motive through I' only enters at the education decision stage.

3.4 Child Rearing Costs

During the parenting stage, parents incur two types of costs: costs associated with child-rearing and direct costs of education. Following Daruich and Kozlowski (2020), we model the child rearing costs as a nonlinear function of income and the number of children:

$$C(y, n) = c_1 y^{c_2} n^{c_3}, \tag{5}$$

where y is the parental income and n is the number of children. The parameter $c_1 < 1$ captures the fixed cost per child, interpreted as the opportunity cost of parents. The elasticity parameters $c_2 < 1$ and $c_3 < 1$ introduce key nonlinearities. The term c_2 implies that wealthier parents face relatively lower marginal costs due to their ability to buy

[19] This formulation aligns with the literature that uses children's net income as a proxy for their well-being (e.g., De La Croix and Doepke, 2003). It does not require future generations to replicate the preferences or behavior of their parents and simplifies computation without losing qualitative realism.

child-rearing services from the market. Meanwhile, c_3 captures decreasing marginal costs in the number of children, consistent with economies of scale in parenting.

When children turn 16, parents choose whether to invest in their children's education. Note that in Indonesia (during our sample period), it was compulsory to have at least 9 years of schooling. This provides the basis for modeling the education decision after children complete compulsory education.

The education choice is binary: parents either decide that their children pursue further study through high school (until age 18) or not. Selecting high education requires a one-time upfront payment equivalent to the annual education cost ϕ. If no further education is selected, no additional education costs are incurred.

3.5 Intergenerational Private Transfers

Modeling intergenerational transfers in life-cycle settings has been explored in literature, often using frameworks with two-sided altruism. For example, Altig and Davis (1993) introduces mutual utility between parents and children in a simple three-period model. However, even in such stylized settings, incorporating endogenous transfer behavior alongside other life-cycle features such as strategic intergenerational behavior can become analytically intractable.

More recent contributions include Boldrin et al. (2015), who model fertility and transfers in a representative-agent economy without uncertainty, and Barczyk and Kredler (2014), who develop a continuous-time model that enables richer strategic behavior. In contrast, our model features heterogeneous agents and income risk over the life cycle, making endogenous transfer modeling computationally prohibitive. Hence, we treat old age transfers as exogenous. Specifically, each adult child transfers a fixed share $b \in [0, 1]$ of their income to their elderly parents, conditional on surviving and working. This formulation follows Curtis et al. (2015) and reflects informal old-age support norms common in settings like Indonesia.

The total transfer received by parents depends on two factors: the number of adult children (n), and each child's income (y^k), which is in turn determined by education and age. Assuming equal contributions from all children, the total transfer is given by:

$$\text{Transfer} = \sum_{i=1}^{n} T_i(y^k, b, j^k) = bny^k, \tag{6}$$

where y^k is average income per child. The exogeneity of b implies that parents cannot contract directly with children but can influence future support through their decisions on fertility and education investment.

Thus, the private transfer channel links parental investment decisions to expected old age support, creating a motive that complements pure altruism.

3.6 Budget Constraints

Households face an intertemporal budget constraint and are subject to borrowing limits that vary by age and education. At any age j, the budget constraint (of an independent individual) is given by:

$$c + a' + T(y, b, j) = y(e, z, j) + a(1 + r), \tag{7}$$

where c is consumption, a' is savings carried into the next period, and $T(y, b, j)$ is the transfer paid to the elderly parents if the individual is of working age. Earnings y depend on education level e, idiosyncratic productivity shock z, and age j. Individuals receive a return r on assets and face a borrowing constraint:

$$a' \geq \underline{a}_{e,j}. \tag{8}$$

Transfers to parents are modeled as a fixed share b of income and are only paid once their child reaches working age ($j \geq J^t$):

$$T(y, b, j) = by_j \quad \text{if } j \geq J^t. \tag{9}$$

During the parenting stage, the budget constraint of a parent reflects both child-rearing costs and intergenerational transfers:

$$c + a' + C(y, n) + T(e, b, j) = y(e, z, j) + a(1 + r), \tag{10}$$

where $C(y, n)$ is the cost of parenting as defined in Section 3.4.[20]

During the education investment stage, parents face an additional cost if they choose high education for their children:

$$c + a' + C(y, n) + n\phi e' + T(e, b, j) = y(e, z, j) + a(1 + r), \tag{11}$$

where $e' \in \{0, 1\}$ indicates the binary education choice and ϕ is the per-child annual cost of high education.

In old age, individuals receive support from their children. They continue working until age J_r, after which income drops to zero. Their budget constraint is:

$$c + a' = y(e, j) + a(1 + r) + \sum_{i=1}^{n} T_i(y^k, b, j^k), \tag{12}$$

where $y(e, j) = 0, \quad \text{if } j \geq J_r$ and $a' \geq 0$. During this phase, elderly individuals finance consumption from savings, labor income (up to J_r), and transfers received from their adult children.[21]

3.7 Decision Problem

This subsection summarizes the dynamic optimization problem faced by individuals at each life-cycle stage, conditional on their state variables. The structure follows the timing of decisions over consumption and savings, fertility, and education investment.

Working stage ($j = J_w$ to $J_f - 1$): Individuals begin independent life at age $j = J_w$ with initial education state e and initial assets a. They choose consumption c and

[20] The child rearing cost includes both monetary and time costs, as in De La Croix and Doepke (2003).

[21] We do not explicitly model any public pension policy that in country like Indonesia applies only to workers in public sector. According to the Asian Development Bank (ADB, 2012), as of 2010 (during our sample period), there was an absence of a comprehensive national program, leading to a reliance mainly on occupational schemes for employees in the formal public sector (Civil Service Pension Program) and the private sector (Private Pensions), leaving out coverage for the informal sector. The coverage of the Civil Service Pension Program was 4.05% of the overall workforce in 2009, while Private Pensions covered 2.39% of the total labor force in 2008. Also, see Kudrna et al. (2023) for a recent review of the pension policy in East and Southeast Asia, documenting the limited social security policy in Indonesia and other Asian countries.

savings a', solving the following household maximization problem:

$$V_j^w(a,z) = \max_{c,a'} u(c) + \beta\rho_{j+1}\mathbb{E}\left[V_{j+1}^w\left(a',z'\right)\right], \tag{13}$$

subject to

$$c + a' = y(e,z,j) + a(1+r), \tag{14}$$

$$a' \geq \underline{a}_{e,j}. \tag{15}$$

Fertility stage ($j = J_f$): At this stage, individuals choose the number of children n as a discrete choice, along with c and a'. The individual problem is as follows:

$$V_j^f(a,z) = \max_{c,a',n} u(c) + v(n) + \beta\rho_{j+1}\mathbb{E}\left[V_{j+1}^w\left(a',z',n\right)\right], \tag{16}$$

subject to

$$c + a' + C(y,n) + T(b,y,j) = y(e,z,j) + a(1+r), \tag{17}$$

$$a' \geq \underline{a}_{e,j}, \quad n \in \{0,1,...,N_n\}. \tag{18}$$

Note that the period from $j = J_f + 1$ to $j = J_e - 1$ is the parenting period. Parents solve the same problem as in the working stage above, but where n is a state variable and subject to the budget constraint given by Equation (10).

Education Investment Stage ($j = J_e$): Parents decide whether to invest in their children's education, making a discrete choice $e \in \{0,1\}$, in addition to c and a'. Utility includes an investment motive based on expected child income. But if parents decide to invest, it costs them an amount of ϕ. An individual's problem at this education investment stage is as follows:

$$V_j(a,z,e,n) = \max_{c,a',e'} u\big(c\big) + v(n) + \beta\rho_{j+1}\mathbb{E}\left[V_{j+1}\left(a',z',e,n\right)\right] + g(n)\left\{u\left(I'\right)\right\}, \tag{19}$$

subject to

$$c + a' + C(y,n) + n\phi e' + T(b,y,j) = y(e,z,j) + a(1+r). \tag{20}$$

$$a' \geq \underline{a}_{e,j}. \tag{21}$$

Old Age ($j \geq J_o$): Elderly individuals no longer make fertility or education decisions. They choose c and a', consuming out of savings, labor income (if $j < J_r$), and transfers from children, according to:

$$V_j(a,e) = \max_{c,a'} u(c) + v(n) + \beta\rho_{j+1}V_{j+1}\left(a',e\right), \tag{22}$$

subject to

$$c + a' = y(e,j) + a(1+r) + \sum_{i=1}^{n} T_i(y^k, b, j^k), \tag{23}$$

$$y(e,j) = 0 \quad \text{if } j \geq J_r, \tag{24}$$

$$a' \geq 0. \tag{25}$$

4 Parameterization of Benchmark Economy

Having outlined the structure of the model, we now turn to its quantitative implementation. In this section, we parameterize the benchmark economy to match key features of Indonesian household behavior. The aim is to estimate a model that replicates observed patterns in fertility and education investment across education and income groups.

We proceed in two steps. First, we externally estimate parameters that can be directly identified from the data, including earnings processes, mortality rates, education costs, and the level of intergenerational transfers. Second, we calibrate a subset of preference and cost parameters internally by matching simulated moments to observed data from the IFLS.[22]

The model is solved numerically using standard value function iteration, and the algorithmic details are provided in Appendix A. The resulting parameterized benchmark model not only reproduces key patterns in the data but also forms the basis for the counterfactual analysis conducted in later sections.

4.1 Externally Estimated Parameters

This subsection describes how we estimate the parameters that can be directly identified from the data. These include the earnings process, mortality rates, education costs, initial conditions, and intergenerational transfer rates. All are estimated using the IFLS, complemented by external sources where needed.

Earnings Profile Estimation We begin by estimating age-earnings profiles separately for individuals with low and high education levels. Using data on male household heads, we estimate a standard Mincer-type regression with a 7-year gap between observations:

$$log(y^e_{i,j,t}) = \beta_0 + \beta_1 j_i + \beta_2 j_i^2 + \gamma H' + z^e_{i,j,t}, \tag{26}$$

where $\log(y^e_{i,j,t})$ is the log annual real income of individual i at age j in year t, and H' includes other observable characteristics such as marital status and location. The residual $z^e_{i,j,t}$ captures unexplained income variation.

Earnings Process Specification To model earnings uncertainty, we follow Storesletten et al. (2004) and decompose the residual component into three parts:

[22] Specifically, we target data moments from a cohort of Indonesian households whose household head is male and was born between 1955 and 1974.

$$z_{i,t}^e = \alpha_i^e + m_{i,t}^e + \epsilon_{i,t}^e, \tag{27}$$

where α_i^e is an individual fixed effect realized at labor market entry, $m_{i,t}^e$ is a persistent AR(1) shock, and $\epsilon_{i,t}^e$ is a transitory shock. The persistent component evolves as follows:

$$m_{i,t}^e = \rho^e m_{i,t-1}^e + u_{i,t}^e, \tag{28}$$

with $m_{i,0}^e = 0$, $\alpha_i^e \sim N(0, \sigma_\alpha^2)$, $u_{i,t}^e \sim N(0, \sigma_{u,e}^2)$, and $\epsilon_{i,t}^e \sim N(0, \sigma_{\epsilon,e}^2)$. All components are allowed to vary by education level.

We estimate these parameters using the Simulated Method of Moments (SMM), targeting the empirical variance-covariance structure of residual earnings across ages.[23]

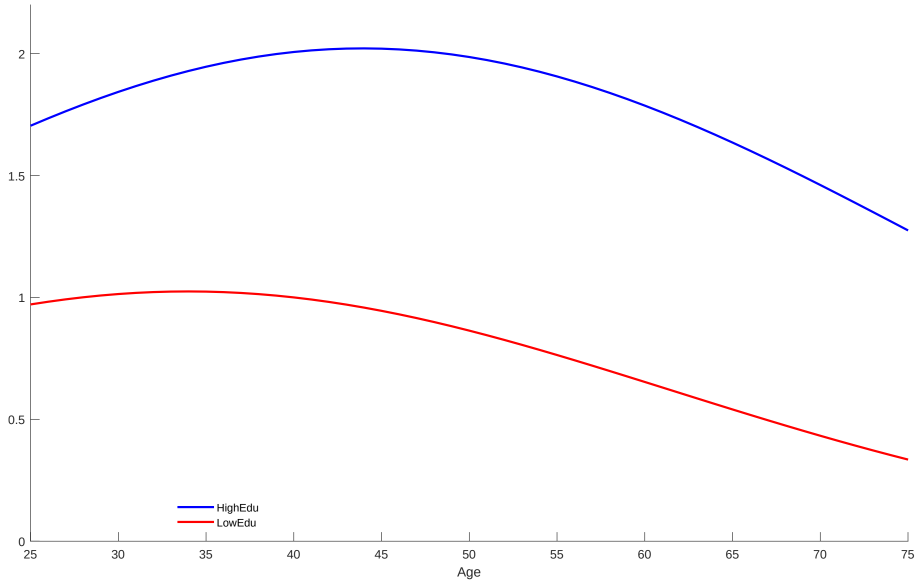


FIGURE 5: Earnings Profiles by Education Level

Note: Predicted earning profile by age using IFLS 2000-2014. Earnings are normalized to the low-educated at age 40.

Estimation Results for Earnings Figure 5 shows predicted (mean) earnings by education group.[24] Earnings exhibit a standard hump shape, increasing with age and peaking in midlife. High-educated individuals earn more and have steeper income

[23] Details are provided in Appendix A.

[24] All earnings are normalized by those of low-educated workers at age 40.

Table 4: Estimates of Income Process

Parameter	Low-educated	High-educated
ρ	0.990	0.961
σ^2_α	0.292	0.292
σ^2_ϵ	0.567	0.478
σ^2_u	0.007	0.019

Note: We target only those moments to which at least 50 observations contribute, which leaves us with more than 80 moments for the low-educated and 59 for the high-educated for Indonesia. α_i is the fixed effect that is realized at the beginning of the life cycle, capturing the variation in initial conditions such as innate ability and retained throughout the individual life. The variables $z^s_{i,t}$ and $\epsilon^s_{i,t}$ are referred to as persistent and transitory life cycle shocks, which are realized at each period over the life cycle.

trajectories, reflecting higher returns to experience. The gap in mean earnings between high-educated and low-educated workers increases over the life cycle.

The results indicate that income shocks are more persistent for low-educated individuals ($\rho = 0.99$), meaning that the shocks last longer. However, high-educated workers experience larger persistent shocks ($\sigma^2_u = 0.019$ vs. 0.007 for low-educated workers). The transitory income variation is higher among the low-educated.

Other External Parameters In addition to the income process parameters discussed above, several other externally estimated inputs are required to calibrate the benchmark economy. These are summarized in Table 5.

Age-specific survival probabilities ρ_j are constructed using WHO life tables, with linear interpolation applied between 5-year age groups. The annual real interest rate is set at $r = 0.05$, based on World Bank averages for Indonesia in the 2000s. Education costs are derived from IFLS 2014 data on schooling expenditures, including tuition and registration fees, and imply that completing high school requires an investment equal to 8.5% of the average income earned by low-educated male workers at age 40. Finally, old-age transfers from adult children to parents are measured using observed net transfers in IFLS 2000–2014; for the 1955–1974 cohorts. These transfers amount to 3.9% of lifetime earnings per child, closely aligning with the 4% benchmark used for China in Curtis et al. (2015).[25]

The next subsection turns to the internally calibrated parameters, which are identified by matching model predictions to targeted moments in the IFLS data.

4.2 Internally Calibrated Parameters

Having estimated parameters directly from the data, we now turn to those that are calibrated within the model. These include preference parameters governing altruism and the cost of child-rearing. We calibrate them by matching simulated outcomes to key empirical moments from the IFLS, using the Simulated Method of Moments (SMM) (i.e., minimizing the distance between the simulated and data moments).

Altruism Parameters As introduced in Section 3.4, parents are altruistic in two dimensions: they value having children (fertility motive) and care about children's future earnings (investment motive). The utility of having children is captured by:

$$v(n) = \lambda_n \log(1 + n),$$

where λ_n governs the strength of the preference for the quantity of children. We calibrate λ_n to match the average number of children observed in the data.

The investment motive enters through the function:

$$g(n) = \gamma_e n^{\kappa_e}.$$

This term multiplies the utility from expected income transfers, as specified in the education investment stage. The parameter γ_e determines the level of altruism towards children's earnings and is calibrated to match the share of parents investing in children's high school education. The curvature parameter κ_e captures how this altruism varies with the number of children and helps to match the fertility gradient between income quintiles.

[25] Using the IFLS waves from 2000 to 2014, we compute the average net transfer from adult children (after age 25) to their parents over the lifetime for the 1955–1974 cohorts, finding that parents receive on average 3.9% of their children's income as old-age support.

Table 5: Summary of Externally Estimated Parameters

	Description	Value	Source/Targeted Moment
Demographics			
	Time period	1	
J_w	Independent age	23	
J_f	Fertility decision age	30	
J_e	Education investment age	46	
J_o	Old age	60	
J_r	Retirement age	75	
J_d	Terminal age	90	
Preferences			
β	Discount factor (annual)	0.96	
μ	Relative risk aversion	0.5	Daruich and Kozlowski (2020)
ρ_j	Survival rates	see text	Estimated (WHO)
Income Process			
	Income profiles	see text	Estimated (IFLS)
ρ^L	Persistence, low-educated	0.990	Estimated (IFLS)
ρ^H	Persistence, high-educated	0.961	Estimated (IFLS)
σ^2_α	Variance of fixed effect	0.292	Estimated (IFLS)
$\sigma^2_{\epsilon,L}$	Variance of transitory shock, low-educated	0.567	Estimated (IFLS)
$\sigma^2_{\epsilon,H}$	Variance of transitory shock, high-educated	0.478	Estimated (IFLS)
$\sigma^2_{u,L}$	Variance of persistent shock, low-educated	0.007	Estimated (IFLS)
$\sigma^2_{u,H}$	Variance of persistent shock, high-educated	0.019	Estimated (IFLS)
Financial Market			
r	Interest rate (annual)	0.05	World Bank
$\underline{a}_{e,j}$	Borrowing constraint	0	
Prices			
$\bar{y}^{L,I}_{40}$	Average income: low-educated at age 40	1	Normalized
ϕ	Educational cost	0.085	Data (IFLS)

Note: Prices are normalized using the average income of a high school dropout at age 40. Recall that IFLS refers to the Indonesia Family Living Survey while WHO refers to the World Health Organization.

Child Rearing Costs Parameters As discussed, we assume that child rearing costs take the functional form:

$$C(y, n) = c_1 y^{c_2} n^{c_3}.$$

Here, c_1 governs the overall cost of raising children and is calibrated to match the average fertility. The parameters c_2 and c_3 shape the elasticity of child costs with respect to income and number of children, respectively, and are the key to replicating the fertility-income gradient observed in the IFLS.

TABLE 6: Values of Internally Estimated Parameters

	Description	Value	Targeted Moment
Altruism			
λ_n	Fertility preference	0.23	Fertility (level)
γ_e	Altruism toward children's income	0.07	Parent-to-child education investment
κ_e	Curvature of altruism	0.60	Fertility by income quintiles
Child Costs			
c_1	Level	0.18	Fertility (level)
c_2	Returns to scale	0.75	Fertility by income quintiles
c_3	Curvature	0.86	Fertility by income quintiles

Estimated Values We estimate six parameters to match nine key moments from the data. As shown in Table 6, the estimated values are generally consistent with those of previous studies such as Daruich and Kozlowski (2020). The estimated child cost elasticities ensure that fertility declines with income, while the altruism parameters shape both fertility and education choices in ways that align closely with observed household behavior.

4.3 Benchmark Model and Data Comparison

With all parameters in place, we simulate the model using an initial sample consisting of 100,000 random draws of individuals. Given estimated income processes, preferences, and constraints, individuals make optimal decisions about consumption, savings, fertility, and education investment over the life cycle.

Lifecycle Behavior The model generates age profiles of consumption and savings that follow the standard hump-shaped patterns widely observed in literature. These profiles, presented in Appendix A, reflect increased income during the prime working years and decreased resources in retirement. Higher-educated individuals consume and save more throughout the life cycle, consistent with their higher earnings.

Fertility and Education Investment Table 7 reports model solutions for fertility and education investment, compared to IFLS data. The model matches the average number of children (2.8), as well as the differences in fertility by parental education. Fertility declines with income, and the share of high-educated children is substantially higher among high-educated parents. The benchmark model closely reproduces fertility patterns by education and income, as well as the distribution of children's education attainment.[26] Minor discrepancies, such as a slightly steeper fertility-income gradient, reflect the parsimonious structure of the model and the trade-offs involved in targeting multiple moments with limited parameters.

Table 7: Model Fit – Fertility and Education Investment

Variable	Model	IFLS Data
Fertility		
– Average	2.8	2.8
– Among low-educated parents	2.9	2.9
– Among high-educated parents	2.6	2.6
Fertility by Income Quintiles		
– Income Quintile 1	3.4	3.5
– Income Quintile 2	3.3	3.1
– Income Quintile 3	3.0	2.8
– Income Quintile 4	2.5	2.7
– Income Quintile 5	1.9	2.5
Share of High-educated Children		
– Among low-educated parents	52.7%	52.8%
– Among high-educated parents	95.0%	94.1%

Note: Income is measured at age 30 (fertility decision stage). High-educated children refer to those who complete high school.

Overall, the benchmark model successfully captures key features of the household behavior observed in the data. It provides a credible foundation for the counterfactual simulations that follow, where we assess the effects of norms around old-age support on fertility and education decisions.

[26] The model also replicates the negative relationship between household wealth and fertility documented in the national-level IHDS 2012 report.

5 Effects of Changing Old Age Support Norms

This section presents results from counterfactual simulations designed to quantify the effects of social norms surrounding old age support on parental decisions. In particular, we assess how changes in the strength of the norm – that is, the fraction of adult children's income transferred to their elderly parents – affect fertility, education investment, consumption inequality among the elderly, and intergenerational mobility of income.

The benchmark model assumes that adult children transfer 4% of their income to their elderly parents (i.e., $b = 0.04$ per child), based on IFLS estimates. To isolate the effect of this norm, we compare the benchmark with two sets of counterfactual scenarios: (i) a setting without any transfer obligations ($b = 0$), mimicking conditions in more formal economies; and (ii) settings with stronger norms ($b = 0.08$ and $b = 0.12$), reflecting higher expectations of family support. All other parameters are kept constant throughout the simulations. By varying b, we can trace how fertility and education investment decisions respond to the perceived strength of old age support norms, and how these micro-level decisions propagate into broader macro-level outcomes such as inequality and mobility.

We begin by examining changes in fertility and investment education decisions at different values of b.

5.1 Fertility and Education Investment Decisions

Table 8 summarizes how fertility, education investment, and asset holdings (specifically a share of those with near-zero asset holdings, representing liquidity constrained households) respond to changes in the strength of the old age support norm b. The benchmark case ($b = 0.04$), estimated from IFLS data, is compared with a no-support scenario ($b = 0$) and two stronger norms ($b = 0.08$ and $b = 0.12$).

We begin with the scenario where there is no old age support ($b = 0$), reflecting a setting without social norms requiring children to support their elderly parents. Compared to the benchmark ($b = 0.04$), average fertility declines by 10.7%, falling from 2.8 to 2.5 children. Education investment also drops, with the overall share of children with a high school education decreasing from 73.3% to 48%. These results indicate that when parents do not anticipate financial support from their children in later life, they reduce both the

Table 8: Summary of Effects as Transfer Norm (b) Changes

Variable description	$b = 0.00$	$b = 0.04$	$b = 0.10$	$b = 0.12$
Panel 1: Fertility				
Average fertility rate	2.5	**2.8**	3.2	3.4
– Among low-educated parents	2.7	**2.9**	3.2	3.3
– Among high-educated parents	2.1	**2.6**	3.4	3.6
Panel 2: Share of High-educated Children[a]				
Average	48.0%	**73.3%**	87.9%	90.4%
– Among low-educated parents	14.7%	**52.7%**	80.8%	85.5%
– Among high-educated parents	75.4%	**95.0%**	96.8%	96.9%
Panel 3: Old Age Transfers[b]				
– Among low-educated parents (60+)	0%	**12.4%**	29.9%	35.1%
– Among high-educated parents (60+)	0%	**16.3%**	40.0%	46.8%
– Among low-educated parents (75+)	0%	**50.7%**	82.2%	87.5%
– Among high-educated parents (75+)	0%	**65.7%**	91.8%	94.7%

Note: Results of benchmark model ($b = 0.04$) are in bold; [a]High-educated children refer to those with high school completion;[b]This refers to the share of parent's total income in old age.

number of children they have and their investment in children's education. Importantly, since parents no longer anticipate any old-age support from their offspring, these decisions are driven solely by altruistic preferences, reflecting the extent to which parents value their children's wellbeing independent of future returns.

The pattern differs by parental education levels. Among low-educated parents, fertility falls modestly from 2.9 to 2.7 (a 6.9% drop), while education investment declines sharply by 38 percentage points (from 52.7% to 14.7%). In contrast, highly educated parents exhibit a larger decline in fertility from 2.7 to 2.4 (a reduction of 11.1%), but a smaller decrease in education investment, which falls by 16.4 percentage points (from 95% to 75.4%). These patterns suggest that low-educated parents are more responsive to the absence of intergenerational support, particularly in their education investment decisions, potentially reflecting both the relatively higher burden of education costs for these households and their greater reliance on children for future economic security.

We now turn to the effects of strengthening the norm. When the old age transfer rate increases to $b = 0.08$ and $b = 0.12$, average fertility rises from 2.8 (benchmark) to 3.2 and 3.4, respectively. The 21.4% increase at the highest transfer rate suggests that fertility decisions are highly sensitive to the strength of the norm. Education investment also responds positively: the overall investment rate rises to 87.9% at $b = 0.08$ and further to 90.4% at $b = 0.12$, indicating that stronger support norms can simultaneously encourage both higher fertility and greater human capital investment.

Disaggregating the results by parental education reveals important heterogeneity. Among highly educated parents, fertility increases markedly by 38.5%, rising from 2.6 to 3.6, while education investment remains relatively stable, reaching a peak of 96.9%. In contrast, among low-educated parents, fertility increases more modestly, by 13.8%, to 3.3, yet education investment rises significantly, from 52.7% to 85.5%, representing an increase of 32.8 percentage points. These findings highlight that while stronger support norms encourage higher fertility across both groups, their effects on education investment are especially pronounced among lower-educated households.

Figure 6 further explores the distributional effects of social norms on fertility by plotting average fertility rates across income quintiles as the strength of the old age support norm b varies. Consistent with earlier findings, fertility tends to increase with stronger support norms. However, the magnitude and direction of this response vary across the income distribution. Fertility rises most markedly in the middle and upper quintiles (Q3 to Q5), while the response among lower-income households (Q1 and Q2) is more muted.[27]

Figure 7 illustrates how education investment responds to the strengthening of intergenerational support norms, disaggregated by parental education, and complements the results in Table 8. Among children of high-educated parents, the share attaining high education increases only marginally as b rises, peaking at 96.9%. In contrast, for children of low-educated parents, the education investment rate increases substantially from 52.7% at the benchmark $b = 0.04$ to 85.5% at $b = 0.12$. This divergence reflects both the stronger marginal returns to combining fertility and education investments as old-age support among low-educated households, and differences in economic flexibility. High-educated parents already start from a high investment baseline (above 90%) and are better able to afford modest increases in response to stronger norms. By contrast, low-educated households face

[27] The non-smoothness in the fertility profiles arises from the model's assumption of discrete fertility choices.

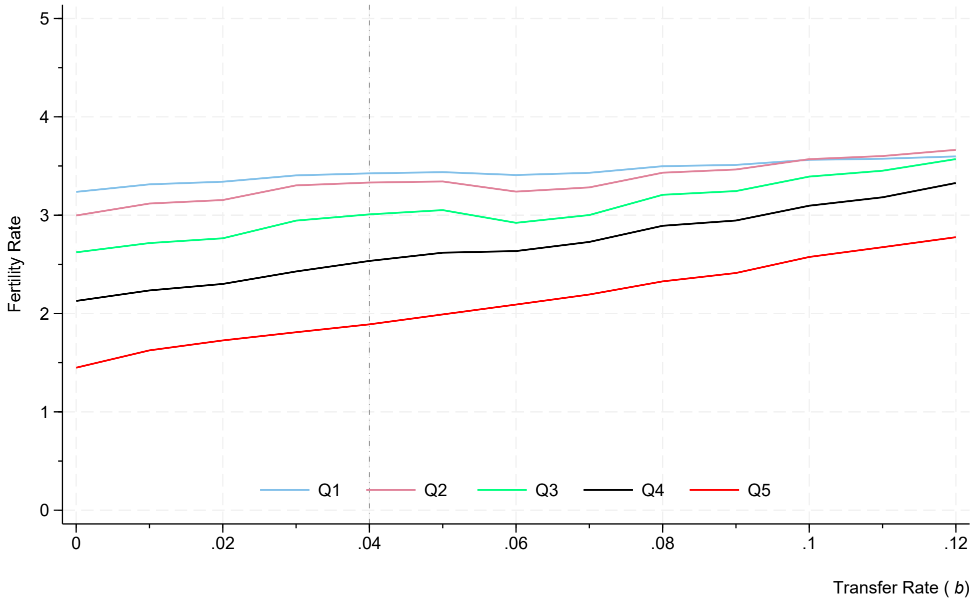


Figure 6: Fertility by Income Quintile

Note: Income is measured at age 30; Benchmark ($b = 0.04$) is depicted by vertical dotted line.

tighter budget constraints and more acute trade-offs between supporting the elderly and investing in their children, making their responses to stronger norms larger.

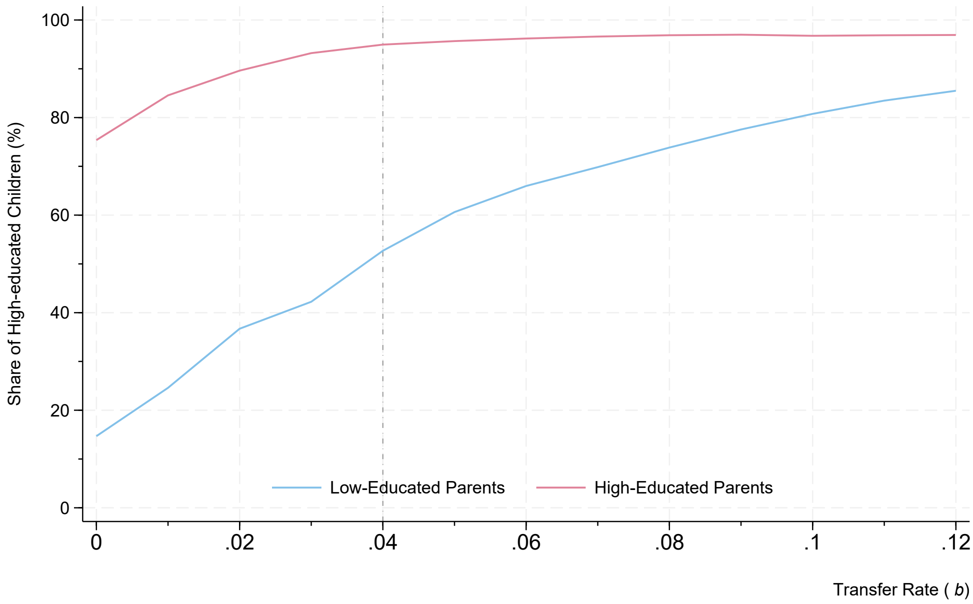


Figure 7: Share of High-educated Children by Parent's Education Type

Note: Benchmark ($b = 0.04$) is depicted by vertical dotted line.

The results in Table 8 and the accompanying figures demonstrate that fertility and education investment are both highly responsive to the strength of intergenerational support norms, but the nature of this responsiveness is asymmetric. The removal of support norms ($b = 0$) consistently reduces fertility and education investment across all groups, with particularly pronounced education investment declines among low-educated households. This implies a persistent education inequality across generations. In contrast, strengthening the norm beyond the benchmark ($b > 0.04$) generates more heterogeneous effects: fertility rises across the distribution, most notably among higher-income and highly educated parents, while education investment increases sharply among low-educated households.[28] These patterns underscore that social norms governing intergenerational transfers not only influence demographic and educational choices but also interact with household resources and constraints, shaping both the level and composition of human capital accumulation and old-age security.

5.2 Old Age Consumption Inequality

Changes in social norms surrounding old age support also significantly influence the composition of income and consumption levels among elderly parents. In particular, stronger norms lead to increased reliance on private transfers from adult children, but they also reduce consumption inequality among elderly parents.

As shown in Table 8 (Panel 3), private transfers, measured as a share of total parental income, increase substantially with the strength of the support norm. For low-educated parents aged 60 and above, this share rises markedly from 12.4% in the benchmark scenario ($b = 0.04$) to 35.1% when the norm is strengthened to $b = 0.12$.[29] Among high-educated parents, the share is initially slightly higher at 16.3%, and increases even more sharply to 46.8% under the strongest norm.

These patterns highlight the pivotal role of parental education in shaping intergenerational financial flows. While low-educated parents rely more heavily on support from

[28] These qualitative patterns remain robust when we vary the discount factor β. Appendix A.4 reports a full sensitivity analysis on the role of β.

[29] It is important to note that the transfer rate observed in the benchmark simulation is not directly comparable to the empirical results presented earlier. The empirical analysis reflects the realized transfers received by the elderly during the 2000–2014 period, whereas the benchmark simulation predicts transfer behavior for the current middle-aged cohort in their future old age. As such, the two capture different cohorts.

their children in old age, high-educated parents exhibit a greater capacity to elicit transfers due to better resource endowments. The widening gap in transfer shares across education groups underscores how norms interact with household resources, mediated through fertility and education investment decisions, to influence old-age security.

This redistribution of resources also affects inequality in old-age consumption. As illustrated in Figure 8, stronger norms reduce consumption inequality among older parents, as measured by the Gini coefficient for those 60 years and older. Specifically, the Gini coefficient declined by 0.03 points, or approximately 6.8%, from 0.43 at the benchmark to 0.40 when $b = 0.12$, indicating a moderate improvement in consumption equality. This reflects the disproportionate gains for low-income parents, whose consumption increases with higher transfer receipts. In contrast, high-income parents, while still benefiting, experience smaller marginal increases. As a result, the income gap between these groups narrows under stronger norms.

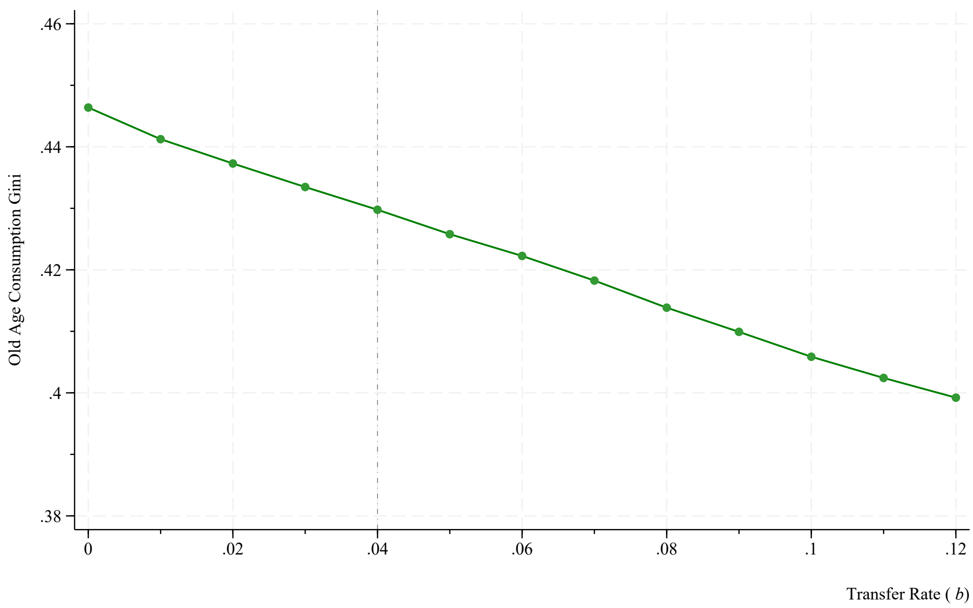


FIGURE 8: Consumption Inequality among Elderly Parents

Note: Benchmark ($b = 0.04$) is depicted by vertical dotted line.

These findings suggest that increased old age transfers – motivated by stronger social norms – enhance the welfare of low-income elderly parents and lead to a more equitable distribution of consumption. They act as an informal safety net, particularly benefiting those at the lower end of the socioeconomic spectrum. This dynamic highlights the redistributive potential of familial support in environments where public provision is limited.

5.3 Intergenerational Mobility of Income

Changes in old-age support norms have important downstream effects on parental decisions regarding fertility and education, which in turn shape intergenerational income dynamics. In this subsection, we examine how mobility evolves as the strength of the support norm varies.

Figure 9 displays the Rank-Rank coefficient, a standard measure of intergenerational mobility, across different values of the transfer rate b. A higher coefficient implies stronger dependence of children's income on parental income rank (i.e., lower mobility), whereas a lower coefficient indicates greater mobility.[30]

We begin by examining the change in mobility when the norm is weakened from the benchmark level ($b = 0.04$) to its complete removal ($b = 0$). The Rank–Rank coefficient remains elevated, only slightly below its peak at $b = 0.02$. This indicates that intergenerational mobility remains limited in the absence of a support norm. The result reflects a situation in which fertility declines, but the reduction in investment incentives, particularly among low-educated households, is not fully compensated for by altruistic motives or other redistributive mechanisms. Consequently, children's economic outcomes continue to mirror those of their parents, and the persistence of income rank across generations remains substantial.

In contrast, strengthening the norm beyond the benchmark level ($b = 0.04$) to $b = 0.12$ produces notable improvements in mobility. Although fertility increases under stronger norms, especially among high-educated parents, gains in educational attainment are more limited in this group, as their investment levels are already high at the benchmark.

[30] The Rank–Rank coefficient provides a popular measure of intergenerational income mobility, assessing the relative position of parents and children in their respective income distributions. Specifically, it estimates the degree of persistence in economic status by regressing the percentile rank of a child's income on the percentile rank of their parent's income:

$$\text{Rank}\left(y_i^{\text{child}}\right) = \alpha + \gamma\,\text{Rank}\left(y_i^{\text{parent}}\right) + \varepsilon_i,$$

where $\text{Rank}(y_i^{\text{child}})$ and $\text{Rank}(y_i^{\text{parent}})$ denote the percentile ranks (ranging from 0 to 100) of child and parent i in their respective income distributions. The coefficient γ captures the strength of the association between generational ranks. A value of $\gamma = 0$ indicates perfect mobility, where a child's relative income position is unrelated to that of their parents, while $\gamma = 1$ implies complete immobility, with full persistence in relative status across generations. In our analysis, income ranks are computed based on labor earnings simulated at age 40 - 43 for both parents and children. The rank–rank coefficient is robust to outliers, less sensitive to measurement error than log–log regressions, and invariant to monotonic transformations of income.

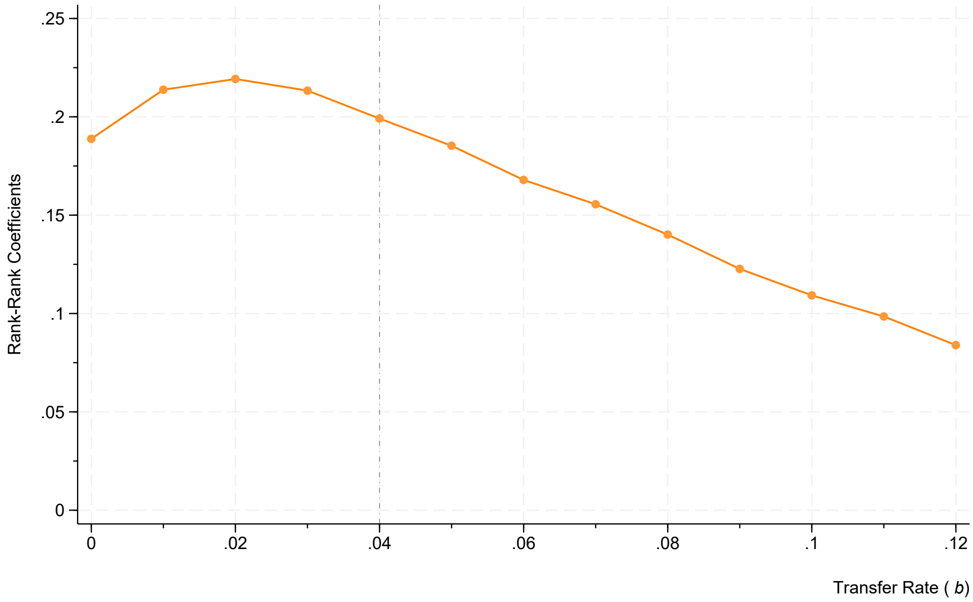


FIGURE 9: Intergenerational Mobility of Income

Note: Benchmark ($b = 0.04$) is depicted by vertical dotted line.

However, for low-educated parents, stronger norms lead to substantial increases in education investment, suggesting that heightened transfer obligations can increase the returns on investing in children's human capital.

Taken together, these findings indicate that strong intergenerational support norms can meaningfully enhance upward mobility, while the absence of such norms can actively hinder it. The key mechanism operates through changes in fertility and education investment decisions, particularly among resource-constrained households, thus influencing the degree of education and income persistence across generations.

5.4 Summarizing Key Mechanisms and Results

The effects of old-age support norms on fertility and education investment are shaped by a set of interconnected economic incentives and constraints. Three primary mechanisms are at play, underpinning the observed behavioral responses.

First, altruism plays a foundational role in household decision-making. Parents derive utility from the well-being and success of their children, which motivates them to invest in education. This altruistic motive operates independently of old-age support expectations:

even when parents do not anticipate receiving future transfers, they still choose to invest in schooling, particularly when returns to education are high.

Second, central to our analysis is the investment motive. In the absence of formal pension systems, children serve as a form of old-age security. When social norms prescribe financial transfers from adult children to their parents, this increases the perceived return to raising children, particularly among low-income and low-educated households. As a result, stronger norms incentivize both higher fertility and greater investment in children's education.

Third, the costs of child-rearing and education also shape parents' decisions. The time and monetary costs of raising children vary across income groups. High-income parents face higher opportunity costs and may prefer to rely on formal savings rather than future transfers. In contrast, low-income parents incur lower costs and obtain higher marginal returns from children, especially when social norms enforce old age support. Education costs are fixed across parent types, making them relatively more affordable for high-income parents.[31]

These interacting mechanisms help explain the asymmetric responses observed in our simulations. The presence of old-age support norms encourages higher fertility and greater educational investment, particularly among households with fewer resources. However, weakening or removing the norm results in sharp declines in both, thereby widening educational inequality, increasing old-age consumption dispersion, and reducing intergenerational mobility.

Importantly, old-age support norms play an implicit redistributive role in economies with limited formal safety nets. By redistributing resources from working-age children to their aging parents, especially those with lower education and income, these norms reduce consumption inequality in old age and buffer against poverty. Yet because strengthening such norms is not realistic, the analysis highlights the dual protective and constraining dimensions of social norms for policy design.

[31] Borrowing constraints may further amplify these effects by limiting the ability of financially constrained households to smooth consumption over the life cycle. While anticipating future transfers might encourage these households to invest more in fertility and education, the simultaneous burden of supporting both children and elderly parents can restrict their capacity to do so.

These dynamics raise an important policy question: to what extent can targeted interventions offset the trade-offs imposed by weakening norms? While our analysis demonstrates that old-age support norms shape fertility and education decisions, they do so in interaction with other structural constraints, most notably the cost of education. For low-income and low-educated households, even modest education costs may limit the ability to invest in children's human capital, particularly when they are also expected to support elderly parents. In turn, these impacts may serve to perpetuate inequality in education into future generations.

This suggests that reducing education costs could be a powerful lever to mitigate inequality and reinforce intergenerational mobility, especially in contexts where social norms are evolving. We turn to this question next, exploring how lower education costs interact with support norms and household heterogeneity to influence demographic behavior and economic outcomes.

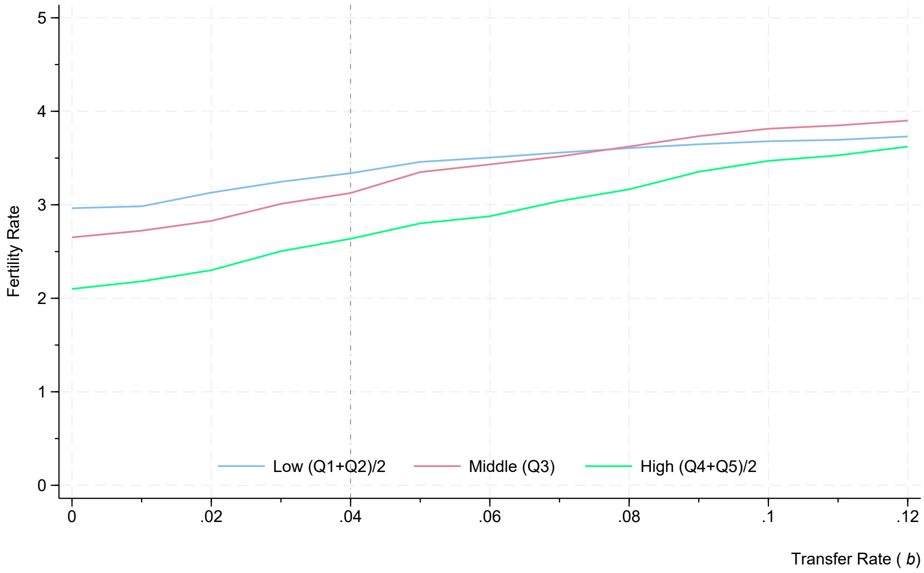
6 Role of Education Cost

This section examines how the education cost parameter ϕ shapes household responses to changing intergenerational support norms, using our life-cycle model with all other parameters held constant. By comparing the benchmark value with lower-cost scenarios, we assess how education costs influence fertility decisions, parental investment in children's human capital, and the resulting patterns of inequality and mobility across generations. The analysis highlights the mechanisms through which education affordability interacts with old-age support norms to produce heterogeneous behavioral and distributional outcomes.

Figures 10 and 11 explore how fertility rates and education investment shares respond to changes in the strength of old age support norms under different values of the education cost parameter ϕ. The benchmark model employs $\phi = 0.085$, and we compare it with lower ($\phi = 0.025$) alternative value.

Several key insights emerge. First, a reduction in education costs leads to higher fertility rates across income groups. With lower education costs, households face fewer financial resource constraints, allowing them to have additional children who can provide old-age support.[32]

(a) Lower $\phi = 0.025$



(b) Benchmark $\phi = 0.085$

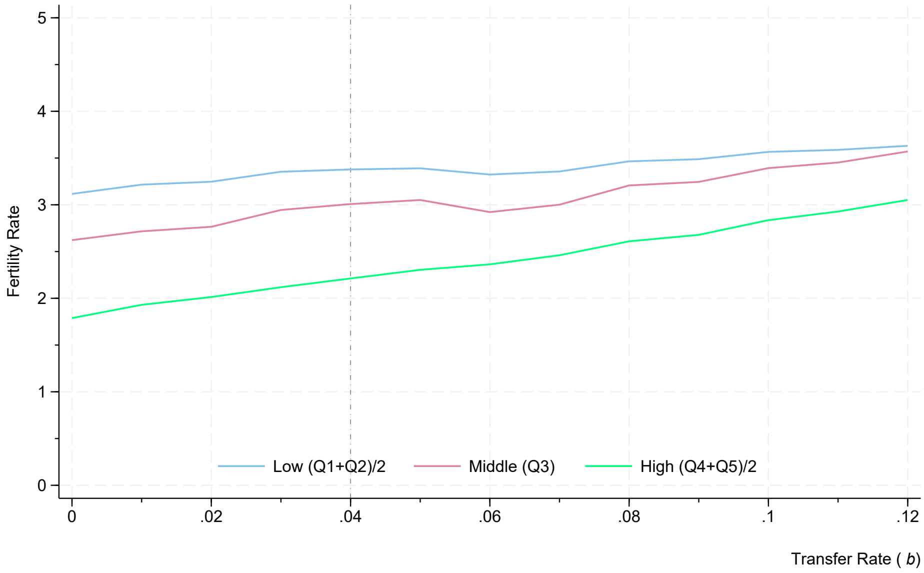
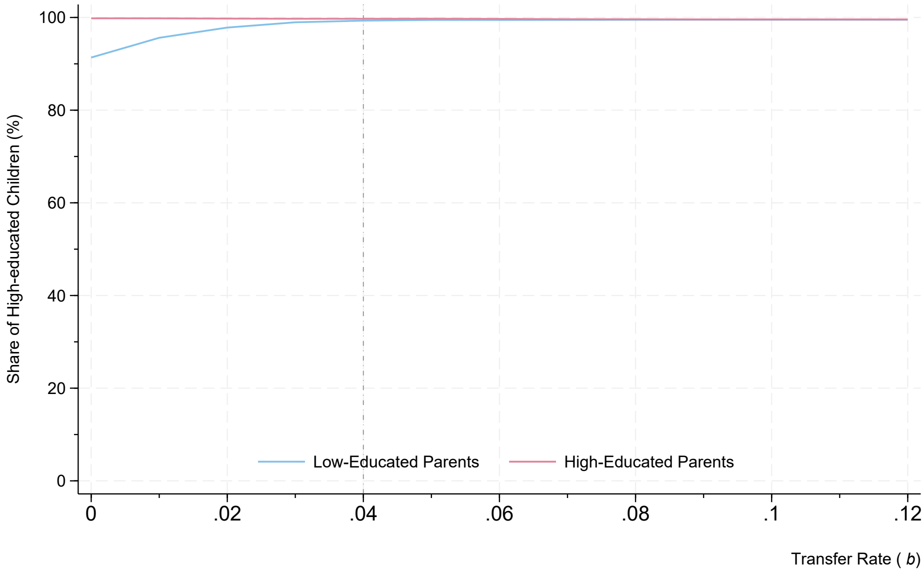


FIGURE 10: Fertility by Income Group as Norm Strength Changes – Role of Education Cost

Note: Benchmark ($b = 0.04$) is depicted by vertical dotted line.

[32] This parallels the effect of increasing the discount factor — see Appendix A.4 with the sensitivity analysis on the role of discount factor.

(a) Lower $\phi = 0.025$



(b) Benchmark $\phi = 0.085$

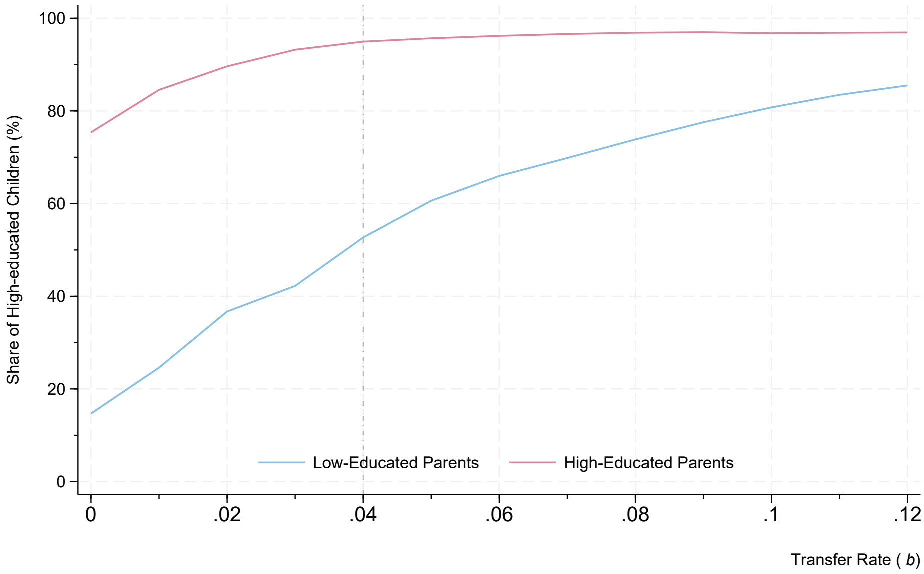


FIGURE 11: Share of High-educated Children by Parent's Education as Norm Strength Changes – Role of Education Cost

Note: Benchmark ($b = 0.04$) is depicted by vertical dotted line.

Turning to education investment, Figure 11 shows that reducing education costs increases children's educational attainment of parents, both low- and high-educated. This effect is especially pronounced among low-educated parents, whose investment rate rises substantially as education becomes more affordable. Lower costs relax their budget constraints and allow greater investment in children's human capital as a means to secure old-age support. For high-educated parents, education investment is already high in the benchmark scenario, and thus the marginal effect of reducing education cost is smaller. However, their investment rates remain stable or increase slightly, consistent with strong baseline incentives and lower sensitivity to changes in educational costs.

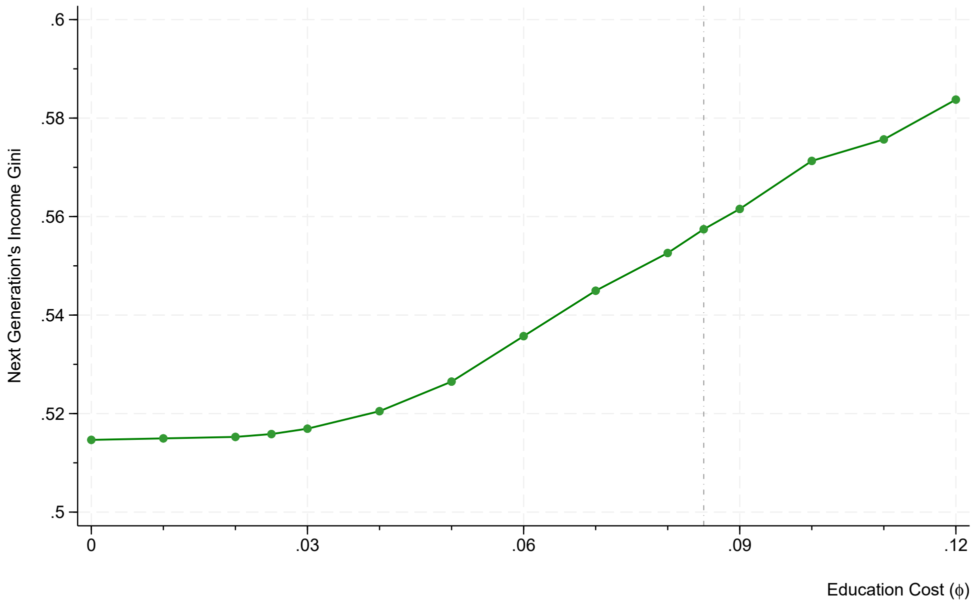


FIGURE 12: Income Inequality among Adult Children – Role of Education Cost

Note: Benchmark ($\phi = 0.085$) is depicted by vertical dotted line.

Second, the responsiveness of fertility to the strength of intergenerational support norms is amplified when education costs are lower, particularly among middle- and high-income households. The slope of the fertility curve steepens under stronger norms in the low-cost scenario, indicating that wealthier households are more willing to expand fertility when the cost of investing in each child is reduced and the expected returns through transfers are high.

Reducing the cost of education has meaningful implications for income distribution and intergenerational mobility. As shown in Figure 12, at the benchmark transfer rate, a lower education cost leads to a noticeable decline in income inequality among adult children. Specifically, the Gini coefficient among the next generation decreases from 0.56 in the benchmark scenario to 0.51 under the lower education cost scenario, a reduction of 0.05

points or approximately 8.9%, which constitutes an economically significant improvement in income distribution. This reflects the fact that more children from low-income households can attain higher education, resulting in a more compressed income distribution in adulthood. The narrowing gap in human capital investment helps equalize opportunities and raises lifetime earnings for disadvantaged groups.

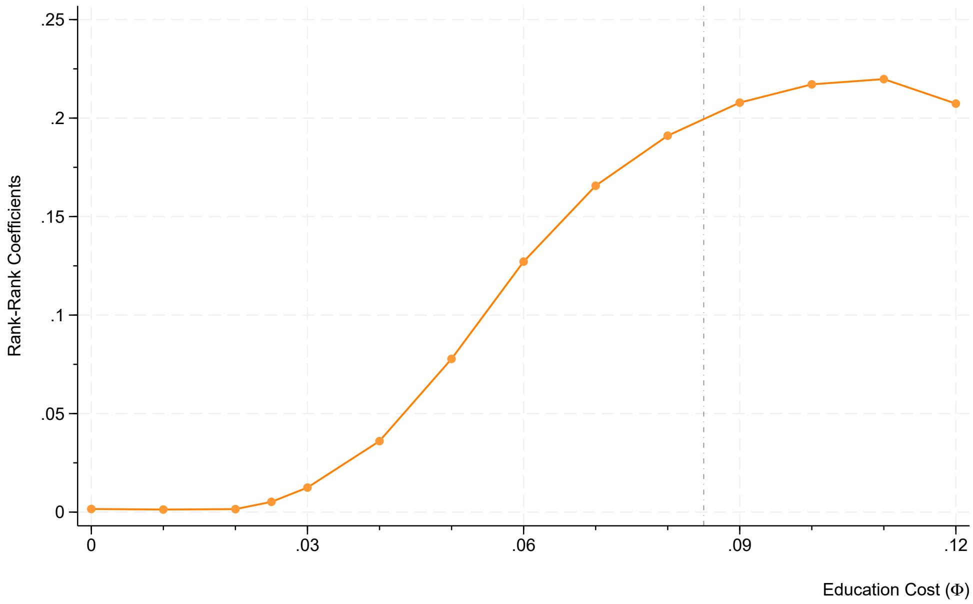


FIGURE 13: Intergenerational Mobility of Income – Role of Education Cost

Note: Benchmark ($\phi = 0.085$) is depicted by vertical dotted line.

In addition to reducing within-generation inequality, lowering education costs significantly improves intergenerational mobility. As shown in Figure 13, the Rank–Rank coefficient, which captures the association between parents' and children's income ranks, declines from 0.19 in the benchmark scenario to zero under both the low education cost and free education scenarios. This implies a complete decoupling of children's income from their parents' economic status, suggesting that educational costs are a key barrier to mobility. The result highlights that when schooling becomes accessible regardless of parental income, especially for liquidity-constrained households, children's future earnings are no longer anchored to their family background. In this sense, the policy not only compresses income inequality but also breaks the intergenerational transmission of disadvantage.

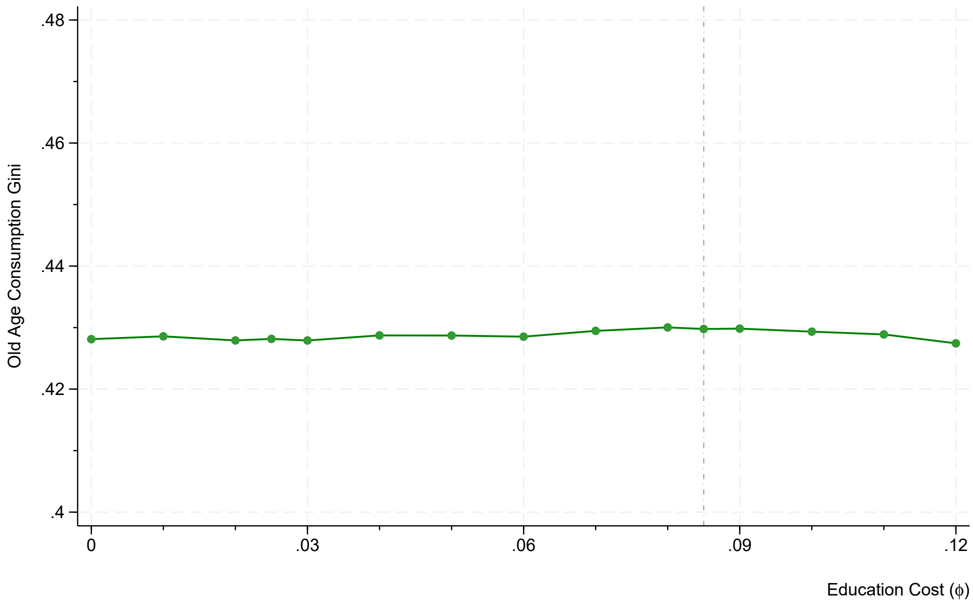


FIGURE 14: Consumption Inequality among Elderly Parents – Role of Education Cost

Note: Benchmark ($\phi = 0.085$) is depicted by vertical dotted line.

However, the effect on current old-age inequality is limited. Figure 14 shows that the Gini coefficient of consumption among elderly parents remains largely unchanged, stable at 0.43. This outcome is expected. While the reduction in education costs makes educational investment more affordable for all parents, especially for low-educated households, it does not fully eliminate underlying resource disparities. Low-educated parents still face tighter budget constraints than their high-educated counterparts. As a result, although low-educated parents increase their education investment substantially, as discussed above, high-educated parents respond by increasing the number of quality children, resulting in larger total transfers in old age. Nevertheless, the reduction in education costs still raises old-age consumption for both groups, and the longer-term effects on inequality may emerge gradually. Greater equality in children's earnings could, over time, lead to more balanced private transfers, thereby contributing to a more equal distribution of consumption among elderly parents in future generations.

In summary, lowering the education cost parameter ϕ enhances both fertility and education investment. The magnitude of these responses varies across income and education levels: fertility responses are more elastic among middle- and high-income households, while education investment gains are especially strong among low-educated parents due to improved affordability. While reducing education costs may not significantly improve the well-being equality of today's elderly, it fosters more equal outcomes for the next generation, both in terms of income distribution and upward mobility, and may contribute to more equitable old-age support in the long run.

7 Conclusion

This paper examines the impact of the social norm of intergenerational support on fertility decisions in developing economies, using Indonesia as an illustrative example. The study constructs a life cycle model that endogenizes fertility and education investment choices and incorporates the expectation of intergenerational transfers from children arising from the social responsibility norm.

Using data from the Indonesia Family Life Survey, we document several stylized facts on fertility and education investment: (i) there is a significant gap in earnings between low- and high-educated individuals; (ii) high-educated parents have fewer children and invest more in their children's education. We also measure transfers from adult children to their aging parents and found that the strength of the old-age support norm was relatively weak in Indonesia in the 2000s, representing approximately 4% of the income of middle-aged individuals. However, despite this modest transfer rate, transfers play a central role in the livelihoods of the elderly, accounting for more than 40% of total income among individuals aged 60 and above – far larger than asset or pension incomes, which remain minimal. This pattern highlights the continued reliance of older cohorts on intergenerational financial support and underscores the economic relevance of the norm we model. In addition, we estimate earnings profiles and uncertainties and ensure that the benchmark model accurately reflects key financial incentives over the life cycle.

We construct a dynamic heterogeneous-agent life-cycle model with endogenous fertility, intergenerational transfers, and human-capital investment. The model builds on the classic quantity–quality trade-off framework, incorporating an exogenous old-age transfer rate and direct altruistic preferences, following the approach of De La Croix and Doepke (2003). Using the endogenous grid method (EGM) for discrete-continuous choices by Iskhakov et al. (2017), we estimate the model to match empirical data moments related to fertility and education investment in Indonesia. The results show that the model can reproduce observed patterns and thus provides a plausible platform for conducting counterfactual experiments.

Overall, the results show that intergenerational support norms play a central role in shaping fertility behavior, education investment, and financial preparedness for old age. Strengthening the support norm – modeled as increasing the required transfer rate from children to aging parents – leads to a substantial rise in fertility and an overall increase in children's educational attainment. This increase in fertility is particularly pronounced among high-educated and high-income households. Conversely, the strongest response in education investment occurs among low-educated households, reflecting substantial improvements driven by higher perceived returns to investing in children's human capital. These changes are accompanied by shifts in private transfers and liquidity constraints, reflecting reallocation of household resources toward children as both a source of utility and a form of future security.

However, empirical evidence points to a weakening of this intergenerational support norm. Simulations demonstrate that eliminating the norm entirely ($b = 0$) significantly depresses fertility and education investment, especially among low-educated households. Such findings emphasize the potential effects of declining intergenerational support norms in developing economies. As traditional expectations of filial responsibility weaken due to modernization, increased labor mobility, and demographic change, families – particularly those with fewer resources – respond by having fewer children and underinvesting in their children's education. These behavioral shifts risk widening disparities in human capital accumulation, reducing old-age consumption security, and perpetuating education inequality across generations, ultimately reinforcing intergenerational persistence in inequality.

In this context, policymakers face a critical challenge: how to support household welfare and intergenerational equity as informal family-based support structures weaken. One possible response is to strengthen formal social protection systems, including the expansion of pension coverage, particularly for informal sector workers who are often excluded from contributory schemes. A growing body of research supports this option. For example, Jung and Tran (2012) demonstrate that extending pension coverage in informal settings can generate significant welfare gains, even in the presence of macroeconomic trade-offs. Bottan et al. (2021) show that pre-existing noncontributory pension programs can act as effective automatic stabilizers during times of crisis, delivering timely support to vulnerable households. However, Hamoudi and Thomas (2014) and Guo et al. (2025) highlight that the introduction of pensions can reshape household behavior – altering coresidence decisions, caregiving responsibilities, and even cultural norms such as son preference. Kudrna et al. (2023) provide an overview of pension policy developments in emerging Asian economies, emphasizing the need to expand coverage and strengthen sustainability amid rapid population aging.

Moreover, our simulations examining the effects of lowering education costs in the context of declining social norms indicate that reducing education expenses effectively counters educational inequalities. The results clearly demonstrate that lower education costs significantly mitigate the adverse impacts associated with weakening intergenerational support norms. Specifically, reducing education expenses leads to increased educational investment and fertility rates, particularly among low-income and low-educated households. Consequently, these improvements foster enhanced human capital accumulation, although the effect on old-age consumption inequality remains limited.[33]

Building upon these insights, this paper expands the scope of social policies that can directly and indirectly influence the well-being of both younger and older generations. While formal pension systems remain critical in providing financial security for elderly individuals, they can be complemented by a comprehensive policy mix that addresses demographic and educational outcomes. Specifically, targeted educational subsidies, incentives promoting investment in children, and policies aimed at reducing liquidity constraints are essential components of this broader strategy. Such interventions are vital not only for maintaining demographic vitality but also for promoting equitable human capital investments and sustaining intergenerational mobility, particularly in contexts where social norms evolve. A more comprehensive exploration of these policy interactions lies beyond the present analysis and represents a promising avenue for future research.

[33] See our discussion in Section 6.

In sum, intergenerational norms are not merely cultural remnants but powerful drivers of fertility, education, and savings behavior. Their erosion has consequences for the welfare of older cohorts and for inequality and social mobility in developing economies. Policymakers must therefore anticipate how shifting family norms interact with household heterogeneity and ensure that institutional reforms compensate for the decline of informal support.

Finally, this study points to several promising directions for future research. First, the strength of social norms is treated as exogenous and fixed. An important extension would be to model the evolution of norms alongside institutional development, such as pension expansion or labor market formalization. Second, the current framework abstracts from old-age income uncertainty, such as health shocks or disability risk. Incorporating these elements would likely reinforce the role of informal and formal support mechanisms in shaping life-cycle decisions. Lastly, while the model is calibrated to Indonesia, it can be readily adapted to other developing countries undergoing demographic transitions and facing similar challenges around aging, informality, and the erosion of traditional family support systems.

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A Appendix

This appendix provides: (A.1) a detailed description of the computational algorithm used to solve the life-cycle model; (A.2) additional information on the construction of earnings measures; (A.3) a full account of the earnings estimation procedure; and (A.4) sensitivity analyses evaluating how fertility and education investment respond to alternative values of the discount factor.

A.1 Computational Algorithm

In what follows, we outline the numerical steps used to solve the model and estimate the parameters.

Solving the model for each individual's income profile

Step 1: Computing the life-cycle income profile

- Generate a normal distribution of income profiles with idiosyncratic shocks, including:
  - Persistent shock in productivity: AR(1) and i.i.d. innovations in log income.
  - Fixed effects: discretize an i.i.d. normal distribution that remains constant over the life cycle.
  - Transitory shock: discretize an i.i.d. normal distribution capturing short-run fluctuations.
- Normalize income to the average income at the median age (40).

Step 2: Solving the model by backward induction using the endogenous grid point method (EGM)

- In the terminal period, the agent consumes all remaining assets: set $a_T = 0$ and $c_T(a) = y_T + Ra_{T-1}$, where T denotes the final age.
- Loop over the choices of fertility ($n \in [1, 2, 3, 4, 5]$) and education ($e' \in [0, 1]$).
- For each combination of fertility and education, use the backward EGM method to capture optimal savings and the associated value function. Specifically:

- Loop over income-shock realizations to construct the probability matrix of earnings transitions.
- For each age t, given the optimal savings at t, loop over the grid of (available) savings at $t-1$.[34]
- Define cash-on-hand as: $x_{t-1} = y_{t-1} + Ra_{t-1}$.
- Construct the Bellman equation and the corresponding stochastic Euler equation.
- Compute optimal choice from the Euler equation: $u'(c_t) = \beta R * \mathbb{E}(u'(c_{t-1}))$.
- Compute the required cash-on-hand. If cash is insufficient, enforce the borrowing constraint by setting $a_t = 0$.
- Construct the savings policy function by mapping calculated values of (a_t, a_{t-1}).
- Store the corresponding utility value for the optimal choice.

- At the end of the loop over e' (for a given n), compute the upper envelope of education choices at the education-decision stage.
- Use this upper envelope to select the optimal e' for each n.
- Similarly, after completing the loop over n, compute the upper envelope over fertility choices at the fertility-decision stage.
- The backward recursion proceeds from T through the age of deciding education and fertility to the initial period $t = 0$.
- At the end of Step 2, the optimal choices of n and e' are obtained for each income profile.
- Store these optimal policies for later simulation.

Simulation and minimizing (weighted) space distance

- Generate an initial sample of $1,000,000$ individuals using random draws of fixed effects and shock realizations.

[34] We use a grid of size 100 with step size 0.01.

- Realize income profiles for each simulated individual.
- Use optimal policy functions to determine fertility and education choices for all simulated individuals.
- Compute the targeted moments implied by the simulated population.
- Compute the weighted sum of squared deviations between model-implied and empirical moments, giving higher weight to fertility moments.
- Estimate the parameters that minimize the weighted distance, yielding the parameter vector closest to the data.

A.2 Earnings Calculation

The methodology for constructing the earnings variable differs for wage earners and self-employed. For wage earners, individual labor income is calculated as the sum of salaries (including bonuses) from both their primary job and any secondary jobs. The IFLS directly collects detailed information on monthly and annual salaries, along with any bonuses, making it a reliable data source.

In IFLS, relevant questions regarding wages can be found in the sheet $b3a - tk2$ for both the main and extra jobs.[35] Specifically:

- Main job:
  - Question $tk25a1$: "What was your approximate salary/wage last month?"
  - Question $tk25a2$: "What was your approximate salary/wage last year?"
  - Question $tk25a2b$: "What was the amount of year-end or other bonuses you received?"
- Extra job:
  - Question $tk25b1$: "What was your approximate salary/wage last month?"

[35] Note that the IFLS 2000 (wave 3) did not include questions on bonuses, so bonuses are assumed to be zero for that wave.

- Question $tk25b2$: "What was your approximate salary/wage last year?"
- Question $tk25b2b$: "What was the amount of year-end or other bonuses you received?"

For self-employed individuals, measuring earnings is more complex as they do not receive regular salaries. Instead, they report the net profit from their personal or household business, where they contribute as a "shareholder." While it can be challenging to distinguish between labor and capital income, for the purposes of this study, we treat their share of net profit as labor income.

In the IFLS, net profit data is collected directly at the individual level.[36] Relevant questions for self-employment earnings include:

- Main business:
  - Question $tk26a1$: "What was the approximate net profit you gained last month?"
  - Question $tk26a3$: "What was the approximate net profit you gained last year?"
- Extra business:
  - Question $tk26b1$: "What was the approximate net profit you gained last month?"
  - Question $tk26b3$: "What was the approximate net profit you gained last year?"

All earnings are reported in Indonesian Rupiah. To account for inflation, earnings from different survey years are converted to real terms using the Consumer Price Index (CPI), sourced from the International Monetary Fund (IMF).

A.3 Earnings Process Estimation

This subsection provides a derivation for the variance-covariance matrix which is used to estimate the earnings process. We first estimate the earnings profile using the proposed

[36] For individuals who were not directly interviewed about their employment status (e.g., employed or self-employed), their share of the household business profit is unavailable. In these cases, earnings are constructed based on their contribution in terms of working hours. However, since a large number of individuals were directly interviewed in the IFLS, we focus only on those with complete employment data and exclude the others.

specification (see Section 4) and acquire the residual of the log earnings, denoted as $y^s_{i,t}$. A time-series process for $y^s_{i,t}$ is then specified to allow different persistence and variance of earnings shocks for different educational levels. Residual earnings are decomposed into a fixed effect (α^s_i); an AR(1) component ($z^s_{i,t}$); and a transitory component ($\epsilon^s_{i,t}$).

$$y^s_{i,t} = \alpha^s_i + z^s_{i,t} + \epsilon^s_{i,t} \tag{29}$$

$$z^s_{i,t} = \rho^s z^s_{i,t-1} + u^s_{i,t} \tag{30}$$

where $\alpha^s_i \sim N(0, \sigma^2_\alpha)$, $\epsilon^s_{i,t} \sim N(0, \sigma^2_{\epsilon,s})$, $u^s_{i,t} \sim N(0, \sigma^2_{u,s})$ and $z^s_{i,0} = 0$.

α^s_i is the fixed effect that is realized at the beginning of the life cycle, capturing the variation in initial conditions, such as innate ability, and retained throughout the individual's life. The fixed effect is different for individuals with different educational levels.

The variables $z^s_{i,t}$ and $\epsilon^s_{i,t}$ (referred to as persistent and transitory life cycle shocks, respectively) are realized at each period over the life cycle. The transitory component encompasses both measurement error and temporary changes in earnings such as bonuses and overtime pay, while the persistent component of idiosyncratic income at age t captures lasting changes in earnings, such as promotions and health status, each period where the individual is affected by a persistent shock of size $u^s_{i,t}$. The magnitude of this shock is governed by the variance $\sigma^2_{u,s}$ and the extent to which it lasts is determined by the persistence parameter ρ^s.

The variance-covariance moments of $y^s_{i,t}$ from the theoretical model can be derived as follows:

Variances:

$$Var(y^s_0) = \sigma^2_{\alpha,s} + \sigma^2_{\epsilon,s} + \sigma^2_{u,s} \tag{31}$$

$$Var(y^s_j) = \sigma^2_{\alpha,s} + \sigma^2_{\epsilon,s} + Var(z_{j,s}) \tag{32}$$

$$Var(y^s_j) = \sigma^2_{\alpha,s} + \sigma^2_{\epsilon,s} + \Big(\sum_{k=0}^{j}(\rho^2_s)^k\Big)\sigma^2_{u,s} \tag{33}$$

Covariances:

$$
\begin{aligned}
Cov(y_{0,s}; y_{j,s}) &= \sigma^2_{\alpha,s} + Cov(z_{0,s}; z_{j,s}) \\
&= \sigma^2_{\alpha,s} + \rho_s^j Var(z_{0,s}) \\
&= \sigma^2_{\alpha,s} + \rho_s^j \sigma^2_{u,s} \qquad (34)
\end{aligned}
$$

$$
\begin{aligned}
Cov(y_{n,s}; y_{j,s}) &= \sigma^2_{\alpha,s} + Cov(z_{n,s}; z_{j,s}) \\
&= \sigma^2_{\alpha,s} + \rho_s^{j-n} Var(z_{n,s}) \\
&= \sigma^2_{\alpha,s} + \rho_s^{j-n} \left(\sum_{k=0}^{n} (\rho_s^2)^k \right) \sigma^2_{u,s} \qquad (35)
\end{aligned}
$$

Estimation is done by minimizing the distance between the moments from the theoretical variance-covariance structure and the corresponding moments in the data. In particular, we target all the variance and covariance terms over age and adopt a minimum number of contributions rule to eliminate moments that are not reliable. More precisely, only those moments to which at least 50 observations contribute are targeted, which leaves us with more than 86 moments for the high educated workers and 50 for the low educated workers in Indonesia.

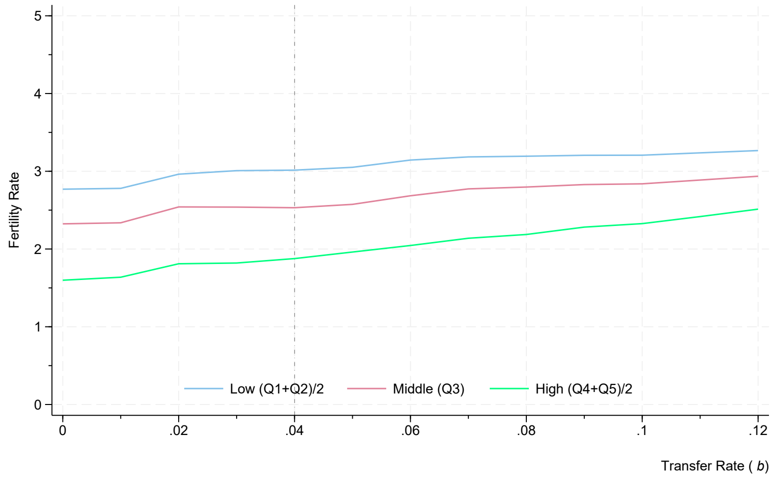
A.4 Sensitivity Analysis on the Role of Discount Factor

This subsection investigates the sensitivity of key results – changes in fertility and education investment decisions as the old age transfer norm changes – to variations in the discount factor β.

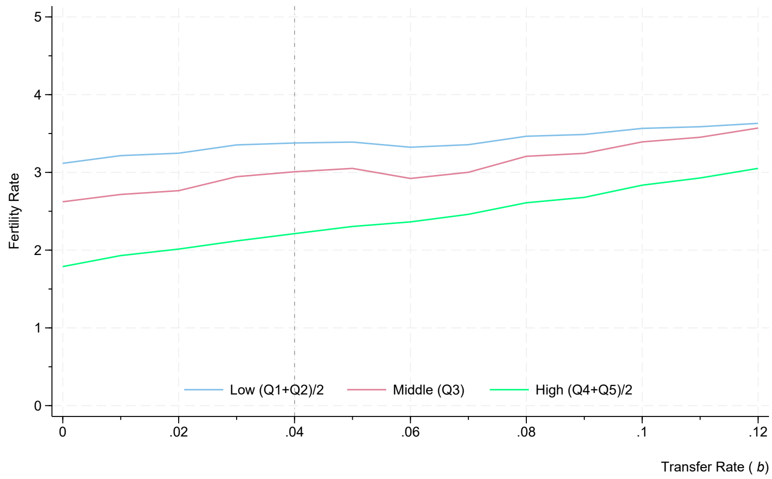
Figures 15 and 16 explore how fertility rates and education investment shares respond to changes in the strength of old age support norms under different values of the discount factor β. The benchmark model employs $\beta = 0.96$, and we compare it with lower ($\beta = 0.95$) and higher ($\beta = 0.97$) alternative values.[37]

[37] A change in the discount factor from 0.95 to 0.97 corresponds to a decline in the implied discount rate from roughly 5.3% to 3.1% per year, using the standard relationship from intertemporal choice theory (Stokey et al., 2019). This represents a sizable change in households' patience and willingness to invest in future well-being.

(a) Lower $\beta = 0.95$



(b) Benchmark $\beta = 0.96$



(c) Higher $\beta = 0.97$

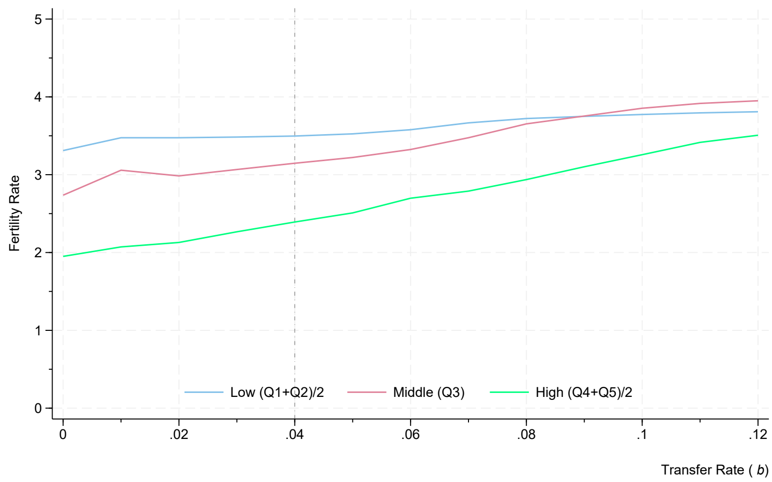
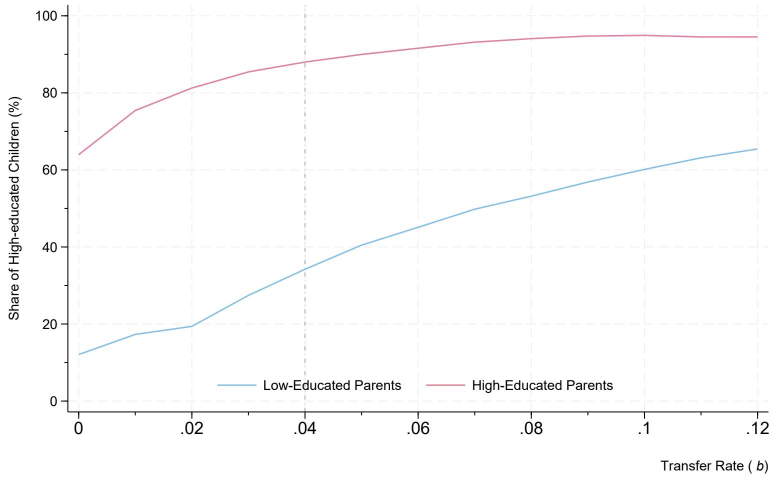
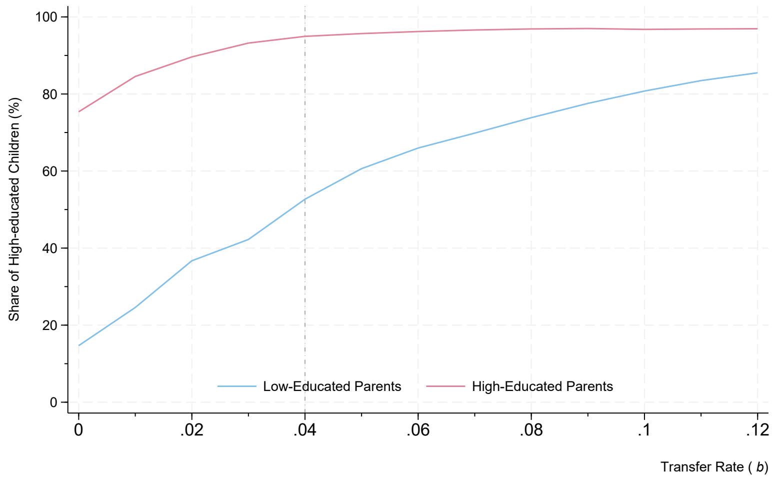


FIGURE 15: Fertility by Income Group as Norm Strength Changes – Role of Discount Factor β

(a) Lower $\beta = 0.95$



(b) Benchmark $\beta = 0.96$



(c) Higher $\beta = 0.97$

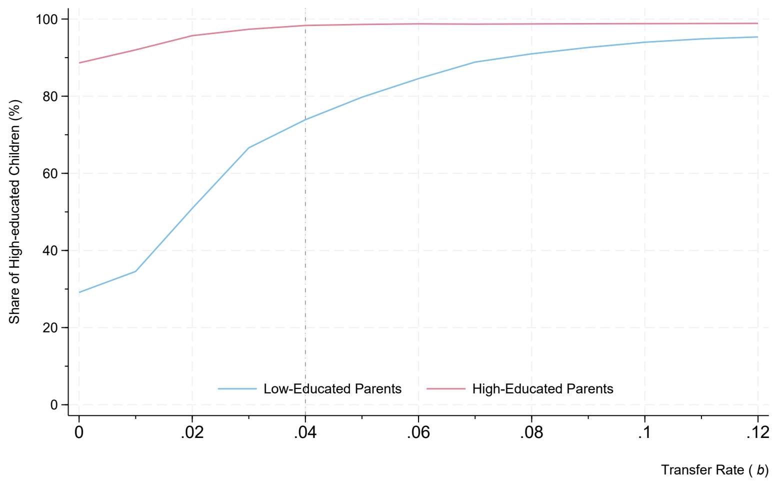


FIGURE 16: Education Investment Share by Parent's Education as Norm Strength Changes – Role of Discount Factor β

Two key insights emerge with respect to fertility behavior. First, higher values of β consistently lead to higher fertility rates across income groups, even when controlling for other parameters. This is intuitive: a higher discount factor implies that individuals place more value on future consumption, increasing the incentive to have children who can provide financial support in old age.

Second, the responsiveness of fertility to the strength of old-age support norms is amplified at higher discount factors, particularly among middle- and high-income households. Comparing the slopes of the fertility curves across different β values shows that as β increases, the fertility response to stronger norms becomes steeper, especially in the upper income quintiles. This suggests that wealthier households are more sensitive to future returns from intergenerational transfers when they are more patient.

Turning to education investment, Figure 16 shows the relationship between education investment shares and norm strength across different discount factors, separately for low-educated and high-educated parents.

Several important patterns are evident. First, higher discount factors systematically increase the share of parents investing in their children's education, for both education groups. When future consumption is valued more highly, parents are more willing to incur current costs for long-term educational gains.

Second, the effect of norm strength on education investment is more pronounced for low-educated parents as β increases. This group is more dependent on old age support, and the incentive to ensure well-earning children is particularly critical when future returns from modest transfers (up to the benchmark transfer rate $b = 0.04$) are valued. For high-educated parents, while the investment in education for their children remains high across all values β, the incremental effect of strengthening the norms is smaller. Their baseline tendency to invest in education is already high due to expected returns, making them less sensitive to variations in norms.

In summary, increasing the discount factor enhances both fertility and education investment behaviors, but the degree of responsiveness varies between income and education distributions. Fertility responses are sensitive among middle- and high-income groups, whereas education investment changes are more noticeable among low-educated parents.