# RESEARCH DIVISION

*Working Paper Series*

## Explaining Intergenerational Mobility: The Role of Fertility and Family Transfers

**Diego Daruich**
**and**
**Julian Kozlowski**

Working Paper 2018-011C
https://doi.org/10.20955/wp.2018.011

June 2018

**FEDERAL RESERVE BANK OF ST. LOUIS**
Research Division
P.O. Box 442
St. Louis, MO 63166

# Explaining Intergenerational Mobility: The Role of Fertility and Family Transfers

Diego Daruich
Federal Reserve Bank of St. Louis

Julian Kozlowski*
Federal Reserve Bank of St. Louis

October 29, 2018

**Abstract**

Poor families have more children and transfer less resources to them. This suggests that family decisions about fertility and transfers dampen intergenerational mobility. To evaluate the quantitative importance of this mechanism, we extend the standard heterogeneous-agent life-cycle model with earnings risk and credit constraints to allow for endogenous fertility, family transfers, and education. The model, estimated to the US in the 2000s, implies that a counterfactual flat income-fertility profile would—through the equalization of initial conditions—increase intergenerational mobility by 7%. The impact of a counterfactual constant transfer per child is twice as large.

JEL Classifications: J13, J24, J62, D91.

Keywords: Intergenerational mobility, Inequality, Fertility

*ddaruich@nyu.edu; kozjuli@gmail.com. We are grateful to our advisors, Raquel Fernandez, Ricardo Lagos, and Gianluca Violante. For helpful comments, we thank Matthias Doepke, Simon Mongey, Pau Roldan, Edouard Schaal, Laura Veldkamp, and Venky Venkateswaran. We also received valuable feedback from participants at seminars at Brown University, New York University, Di Tella University, ECINEQ 2015, EEA 2015, the 2015 Chicago Summer School on Socioeconomic Inequality, the Fall 2015 Midwest Macro Meeting, SED 2016, and the Families and the Macroeconomy Conference 2018. The views expressed are ours and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors.

What factors determine intergenerational mobility? Is income inequality mainly due to differences in the opportunities available early in life or to adult income risk? We study the sources of income inequality and intergenerational mobility with particular interest in the impact of families. Extensive empirical evidence shows that family choices are heterogeneous and correlated with family characteristics: Poor families tend to have more children (e.g., Jones and Tertilt, 2008) and invest fewer resources toward their children than rich families (e.g., Altonji et al., 1997). First, this heterogeneity in family choices can lead to differences in education outcomes, leading to higher levels of inequality relative to an economy without such heterogeneity. Second, this correlation can lead to lower intergenerational mobility, as the children of richer parents have more resources available for education. To evaluate the quantitative importance of these forces, we build a model in which families face a quantity-quality trade-off between having more children and making larger investments in them. Parents influence children's initial conditions regarding skills and economic resources, both of which shape their education choices and later labor income due to capital market imperfections. The model allows us to study the dynamic interactions between family choices and intergenerational mobility, which is our main contribution.

This paper first explores the empirical evidence on the relation between fertility and income and its consequences on children's education. We use US Census data to exploit the within-country state variation. We confirm that, on average, poor families tend to have more children than rich families. We find, however, that fertility differences between income groups are smaller in richer states. This result is robust to alternative definitions of fertility rates, as well as to different regression specifications. Next, we look at the relation between fertility differentials and children's education outcomes. We use older census data to estimate fertility differentials at the time of birth of individuals. More recent census data is used to evaluate education outcomes for individuals born in those states and time. We find that individuals born in states with larger fertility differentials are associated with lower high-school graduation rates. As education is an important factor for income inequality and intergenerational mobility, these empirical findings suggest that fertility differentials may have aggregate consequences. We estimate a life-cycle model to evaluate if fertility and child investment are important factors driving income inequality and intergenerational mobility.

We introduce endogenous fertility, family transfers, and education in the standard heterogeneous agent life-cycle model, with idiosyncratic income risk and credit constraints in the spirit of Huggett et al. (2011). Parent-to-children transfers will be important in the model for children to access higher levels of education. A key difference relative to Huggett et al. (2011) is that in our analysis, initial conditions—defined as the agents' initial state variables—are endogenously related to parental background. This change allows us to study intergenerational mobility.

The model incorporates five sources of intergenerational persistence. The following two fo these five sources are endogenous and are the main focus of this paper: the choices of (i) number of children and (ii) parent-to-child transfers, both of which affect the resources available for each child's education and, hence, their labor income. In addition, the model includes the following three sources of exogenous persistence: (iii) the initial human capital (i.e., at age 14 in the calibrated model) is related to parental human capital and directly affects income; (iv) the school taste is related to parental education and affects education choices; and (v) adult income shocks, which reduce the importance of initial conditions for labor earnings.

We estimate the model to the US in the 2000s and use it to analyze the impact of individuals' initial conditions. To estimate the novel elements in our model, we fit moments on the relationship between fertility and income, family transfers, and intergenerational mobility. A set of validation exercises shows that the quantitative model is consistent with both not-targeted moments and cross-state evidence on the relationship between average income, fertility, and education. The variation in lifetime earnings—a measure of income inequality—can be decomposed into differences in initial conditions and in labor-income shocks. Our model suggests that the variation in lifetime earnings due to differences in initial conditions is 60%. In other words, 60% of lifetime-earnings inequality in the US can be attributed to family background.

What are the forces driving this result? Our estimated model allows us to study the quantitative importance of both endogenous and exogenous sources of income inequality and intergenerational persistence. First, we solve an alternative model in which fertility is exogenous and constant across families. This exercise reveals that in the baseline economy, fertility accounts for 1% of the variance of log-lifetime-earnings and up to 2% of the variance of log-income for young individuals. Fertility differentials also account for 7% of the intergenerational mobility observed in the data—this difference is equivalent to approximately one-third of the standard deviation in intergenerational mobility across commuting zones (Chetty et al., 2014). Second, we simulate an economy in which fertility is endogenous, but transfers from parents to children are exogenous and constant (at the average level). These transfers play a major role in the observed inequality and social mobility in the US. The impact on inequality and mobility of this counterfactual constant transfer per child is twice as large as the ones from the constant fertility counterfactual.

Effects, however, are heterogeneous for children with different family backgrounds. Children from low-income and low-educated parents are those with fewest resources and most siblings. They are, therefore, the most affected by the constant fertility or constant transfers counterfactuals. With either counterfactual, children born to bottom-income-quintile parents exhibit a lower probability of remaining in the bottom quintile, while children of top-income-quintile parents have a larger probability of dropping to the bottom quintile. Even though effects are heterogeneous, the aggregate distribution of education shifts toward an economy with fewer high school dropouts and more high school graduates, decreasing income inequality and increasing intergenerational mobility.

Both of these counterfactuals operate through the distribution of initial conditions, particularly initial assets (or parental transfers) and human capital. With a counterfactual flat income-fertility profile there are relatively fewer children born from poor households. As fewer children are born with low levels of initial human capital and assets, the initial distribution becomes more homogeneous. First, an equalized initial distribution of assets leads to an increase in access to education. Since wages depend on education, this implies lower labor-income inequality. Second, a more homogeneous initial distribution of human capital directly leads to lower labor-income inequality (independent of education). Note that in this counterfactual there are fewer children born from poor families, and these children now have higher levels of initial assets (parental transfers), which increases intergenerational mobility. With counterfactual constant transfers per child, the initial distribution also becomes more homogeneous, reducing inequality and increasing mobility through similar mechanisms. Our findings suggest that to understand income inequality and social mobility, one should take fertility differentials and family transfers into account.

Finally, we also study the role of the three exogenous shocks that take place across the agent's life-cycle: initial human capital, school taste, and adult income shocks. Among these, the stochastic process behind the initial human capital is the most important determinant of inequality and intergenerational mobility. The main objective of this paper, however, is to study the role of fertility and family transfers, so we model this stochastic process as an exogenous shock disciplined by the data. Nevertheless, our results suggest that policies that affect initial human capital may also have sizable effects on fertility and transfer choices. Thus, studies of human capital policies that abstract from family transfers and fertility choices may be biased in their results.

**Related Literature** This paper relates to two literatures usually studied in isolation: income inequality and intergenerational mobility. However, there is a strong and positive correlation between the two (Corak, 2013). On the one hand, models of inequality typically focus on adult shocks and abstract from endogenous initial conditions (e.g., Keane and Wolpin, 1997; Huggett et al., 2011). On the other hand, models of intergenerational mobility usually focus on initial conditions and abstract from adult income volatility (e.g., Restuccia and Urrutia, 2004; Lee and Seshadri, 2018). Both initial conditions and labor-income volatility generate income inequality. We contribute by providing a model that combines these two sources and assess their relative importance, which also allows for the joint study of inequality and mobility.[1]

The closest paper to ours is Huggett et al. (2011), in which the authors use a Bewley model to study the sources of inequality. They find that most of the income inequality is due to conditions present before entering the labor market. These conditions, however, are exogenous in their analysis, implying that their results are silent about the forces that determine inequality

[1]The literature on quantitative models combining adult uncertainty and endogenous initial conditions is scarce. See Yum (2018), Daruich (2018), and Lee and Seshadri (Forthcoming) for some relevant exceptions.

of opportunity. Parental environment and investments have been shown to be determinants for childhood development and their adult outcomes (Murnane et al., 1995; Cunha et al., 2010). Hence, modeling family choices is necessary to study the origin of conditions early in life. Our model endogenizes these earlier stages of life through choices regarding education, fertility, and family transfers. By incorporating intergenerational linkages, we are able to explore the role of family background forces that may determine inequality and intergenerational mobility.

We study the impact of fertility choices on inequality and social mobility.[2] Our model highlights a quantity-quality trade-off à la Barro and Becker (1989) as a main determinant of initial conditions. There is evidence that poor families have more children than richer ones—i.e., there is a negative elasticity of fertility to income (Jones and Tertilt, 2008). We contribute to this literature by showing that this elasticity is smaller for richer states within the US. We also find that children born in states with larger fertility differentials are associated with lower education outcomes. Our quantitative model is consistent with these empirical findings.[3]

Several papers explore the effect of inequality on human capital accumulation (or growth) through fertility choices (e.g., de la Croix and Doepke, 2003, 2004, 2009; Moav, 2005). In these papers, inequality affects growth negatively through its interaction with fertility choices. We complement this literature by exploiting a similar mechanism between fertility choices and adult outcomes to study, instead, the effect of fertility differentials on inequality and intergenerational mobility.

The rest of the paper is organized as follows. Section 1 presents our empirical findings on fertility differentials and education. Section 2 introduces the model, and Section 3 explains its estimation and conducts some validation exercises. The model's results on inequality and intergenerational mobility are presented in Section 4. Finally, Section 5 concludes. The Appendix contains

[2]Note that we focus on labor-income inequality and do not look into wealth inequality. Recent literature also finds a decisive role for family background in explaining wealth inequality (Nardi and Yang, 2016; Benhabib et al., 2015). We also abstract from sorting, another force that has been used to generate inequality through families (e.g., Fernandez and Rogerson, 2001; Fernandez et al., 2005) and from detailed early-childhood human-capital formation, as in Lee and Seshadri (Forthcoming) and Daruich (2018).

[3]Quantitative models in the fertility literature include Manuelli and Seshadri (2009) and Roys and Seshadri (2014), which are used to explain differences in average fertility rates across countries and long-term economic growth, respectively. Nevertheless, both abstract from uncertainty, and though heterogeneity is allowed in the second one, it is only in the form of constant skill differences across dynasties.

additional details.

# 1 Empirical Findings

Since we are going to analyze social mobility and income inequality through the lens of a model with fertility decisions, we analyze the data available on these. First, we use Current Population Survey (CPS) micro data to study the trends in the US over time. In our preferred analysis, we use Census data instead to exploit the within-country state variation. We find evidence that (i) at the national level, there is a negative relationship between fertility and income, but it has diminished over time; (ii) states with higher levels of average household income are associated with smaller fertility differentials; and (iii) individuals born in states with larger fertility differentials are associated with lower high-school graduation rates.

If children were considered a normal good, we should observe richer people having more children. However, this is not usually the case. Comparing fertility over time, most countries have experienced a decrease in fertility (as they become richer). Comparing fertility across countries, richer countries tend to have fewer children per family. More interestingly for our study, within a country-year it is also the case that richer people tend to have fewer children. Jones and Tertilt (2008) look at US Census data on women born between 1826 and 1960 and find substantial evidence that the relationship between income and fertility was stably negative. Controlling for several factors (for instance, urban versus rural families, location, or race), they suggest that economic factors play a large role in fertility decisions and that the negative relation with income is robust. We update their analysis for the US using micro data from the CPS—between 1968 and 2013—and census data—between 1960 and 2010—from the Minnesota Population Center (IPUMS). In all our analyses, income is defined as annual income at the family level, while our main measure of fertility is the Total Fertility Rate (TFR).[4]

Let $\text{inc}_{q,s,t}$ and $fert_{q,s,t}$ be the mean income and fertility rate, respectively, of income quantile $q$

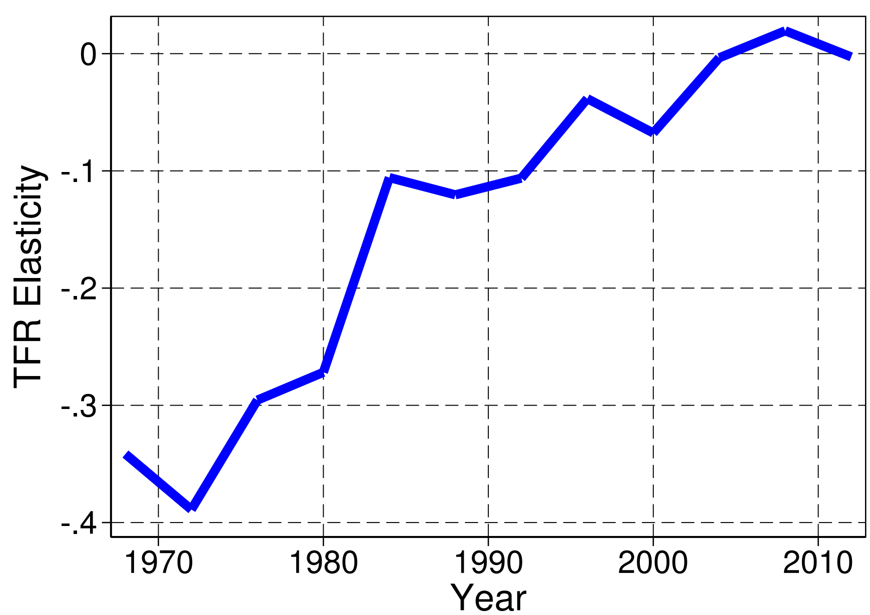
[4] Our measures of fertility and income differ from Jones and Tertilt to be able to study more recent periods. See Appendix A.1 for details.

in region $s$ and year $t$.[5] We allow for region identifier $s$ for our cross-state analysis. We estimate

$$\ln\left(fert_{q,s,t}\right) = \alpha_{s,t} + \beta_{s,t}\ln\left(inc_{q,s,t}\right) + \epsilon_{q,s,t}, \tag{1}$$

where $\beta_{s,t}$ will be referred to as the *elasticity of fertility to income* for region $s$ in year $t$. If this value is negative, richer households tend to have fewer children. Values closer to zero imply that fertility rates are not related to income (at least, according to this specification). Given our main interest on fertility decisions as a function of income, we do not want to mix single-parent households with two-parent households. Hence, we limit our analysis to "marital fertility"; i.e., the fertility of those women who, when they answer the survey, indicate that they are married. Appendix A.2 reports details on the sample selection. Figure 1 shows the evolution of the elasticity of fertility to income for the US, with its value on the vertical axis. Figure 1 not only confirms that fertility elasticity has been negative since 1968, but also suggests that it has decreased over time, implying that the difference in the number of children between poor and rich households has become smaller.

Figure 1: **Elasticity of fertility to income**.

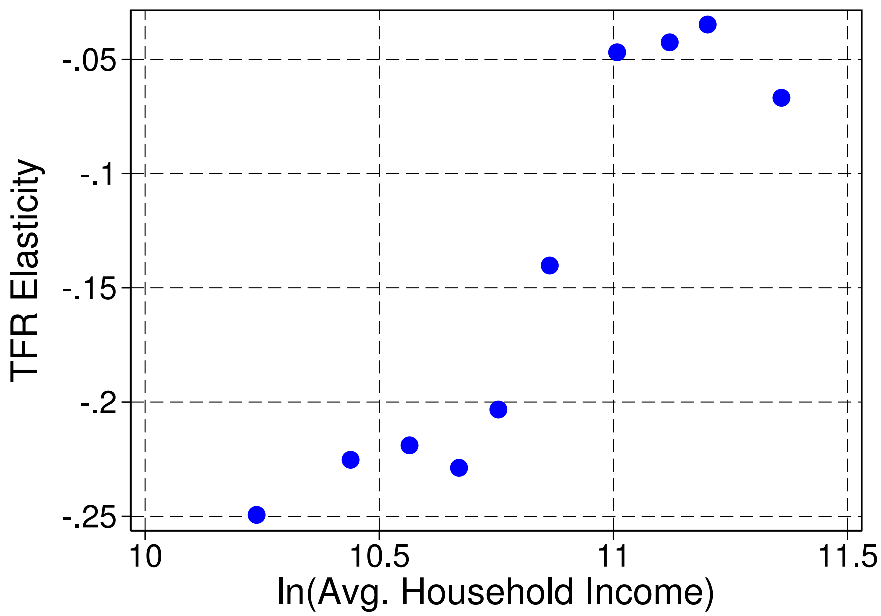



*Source: CPS. Years: 1968-2013. Observations are grouped in 3-year windows. Methodology is explained in the main text.*

[5]Using median income changes the results slightly, but they remain qualitatively the same.

To better understand what is behind this pattern, we extend our analysis to exploit the cross-state variation using US Census micro data from IPUMS; i.e., for each state $s$ and year $t$ we estimate (1). We first analyze the data visually and, then, perform more formal statistical tests. For the visual inspection, we combine all our observations and divide them into deciles according to their levels of real average household income. For each of these groups we calculate the mean household income and fertility elasticity. Figure 2 shows that richer states tend to have elasticities closer to zero or, in other words, smaller fertility differentials.

Figure 2: **Elasticity of fertility to income by average household income**.



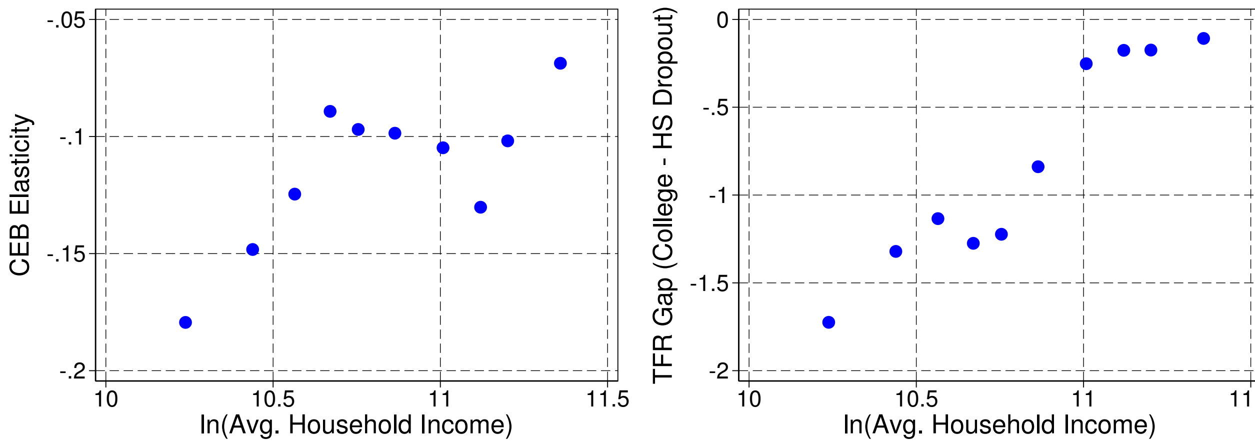

*Source: Census. Years: 1960, 1970, 1980, 1990, 2000, and 2010. We divide observations into deciles according to average household income. For each decile, we calculate the mean level of household income as well as the mean fertility elasticity of income. Figure A.1 in the Appendix includes all of the data observations before grouping them into deciles. Methodology is explained in the main text.*

The pattern of higher fertility differentials being associated with lower average household income is robust to alternative measures of fertility.[6] First, instead of using TFR, we use Children Ever Born (CEB) to compute the fertility elasticity as in (1). The left panel of Figure 3 reports the results. Second, we can use the fertility differences between education groups: We calculate the difference between the TFR of women married to college-graduate men and that of women

[6]See Appendix A.1 for details on each of these fertility measures.

married to high school dropout men. The right panel of Figure 3 reports the results. Qualitative results in both cases are similar to those using the TFR elasticity to income from Figure 2: Richer states are associated with smaller fertility differentials.

Figure 3: **Fertility Differentials: Robustness using alternative measures of fertility**.




*Source: Census. Years: 1960, 1970, 1980, 1990, 2000 (only TFR Gap), and 2010 (only TFR Gap). We divide observations into deciles according to average household income. For each decile, we calculate the mean level of household income as well as the mean fertility differential measure. Figure A.2 in the Appendix includes all of the data observations before grouping them into deciles. Methodology is explained in the main text.*

Various factors related to states' characteristics (e.g., culture) might be driving these results. To attempt to control for these possible concerns, we regress the fertility elasticities on the logarithm of the real average household income, controlling for state and time fixed effects. The regression specification is

$$\text{Fertility Elasticity}_{s,t} = \alpha + \gamma \ln(\text{Avg. Household Income}_{s,t}) + \eta_s + \mu_t + \epsilon_{s,t} \tag{2}$$

where Fertility Elasticity$_{s,t}$ is equal to the estimated $\hat{\beta}_{s,t}$ from (1). Table 1 shows that the elasticity of fertility (TFR) is increasing in real average household income. Once again, this implies that richer states are associated with smaller fertility differentials. This relationship seems stable and robust to controlling for state fixed effects and time fixed effects. This suggests that the pattern seen in Figure 1 may not be due simply to changes over time, but can be thought of as a general relation between average income and fertility differentials.

How do education outcomes relate to fertility differentials? Intuitively, we would expect states

Table 1: **How the elasticity of fertility to income changes with average income**.

| | (1) | (2) | (3) |
|---|---|---|---|
| Ln(Avg. Household Income) | 0.228*** | 0.260*** | 0.243*** |
| | (0.0169) | (0.0184) | (0.0802) |
| Observations | 300 | 300 | 300 |
| R-squared | 0.355 | 0.487 | 0.582 |
| # of States | 51 | 51 | 51 |
| State FE | NO | YES | YES |
| Year FE | NO | NO | YES |

*Robust standard errors in parentheses. *, **, *** denote statistical significance at the 10, 5, and 1 percent level, respectively. Source: Census. Years: 1960, 1970, 1980, 1990, 2000, and 2010. Methodology is explained in the main text.*

with larger fertility differentials to have lower average levels of education. Larger fertility differentials imply that poor families have relatively more children, which would lead to a larger share of children being born with scarce resources. Assuming this affects their education, we would then expect to observe lower average education in states with larger fertility differentials. To test this hypothesis, we focus on the education of individuals born in different states in 1960, 1970, and 1980. For the sake of clarity let's look at how we study children born in 1960. First, we use data from 1960 to calculate the fertility elasticity, average household income, and income inequality in each state in their year of birth (i.e., in 1960). Second, we use data from when that generation is 30 years old (i.e., in 1990) to calculate high-school graduation rates for each state.[7] Table 2 shows that individuals born in states with larger fertility differentials are associated with smaller high-school graduation rates. This result is robust to controlling for mean household income and income inequality present in the state and year in which they were born, as well as for state or year fixed effects.[8] These results suggest that a one-standard-deviation change in the elasticity can explain approximately one-fifth of the standard deviation in high-school graduation rates in the data.

Section 2 will introduce a model that, once estimated, will be consistent with the evidence presented in the current section. Given obvious endogeneity concerns, we will then use the model to evaluate the importance of fertility differentials (and family transfers) for education,

[7]The choice of the age and year of birth is limited by the timing of the Census data.

[8]This evidence complements the findings in Kremer and Chen (2002), who show income inequality and fertility differentials across education groups are positively correlated across different countries.

Table 2: **How education relates to fertility elasticity**.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Fertility Elasticity | 0.0656** | 0.0591** | 0.0325*** | 0.0314*** | 0.0264** |
| | (0.0265) | (0.0243) | (0.0111) | (0.0107) | (0.0108) |
| Ln(Avg. Household Income) | | 0.101*** | 0.0904*** | 0.0803*** | 0.0952** |
| | | (0.0123) | (0.00798) | (0.00848) | (0.0396) |
| Household Income Gini | | | | -0.357* | -0.319* |
| | | | | (0.178) | (0.177) |
| Observations | 151 | 151 | 151 | 151 | 151 |
| R-squared | 0.030 | 0.355 | 0.902 | 0.909 | 0.910 |
| # of States | 51 | 51 | 51 | 51 | 51 |
| State FE | NO | NO | YES | YES | YES |
| Year FE | NO | NO | NO | NO | YES |

*Robust standard errors in parentheses. *, **, *** denote statistical significance at the 10, 5, and 1 percent level, respectively. Source: Census. Years: 1960, 1970, 1980, 1990, 2000, and 2010. We use data from 1990 on to calculate the high-school graduation of individuals born 30 years earlier in each state. We then use data from 30 years earlier to calculate the fertility elasticity, average household income, and income inequality in each of those states. Methodology is explained in the main text.*

inequality, and intergenerational mobility.

# 2 Model

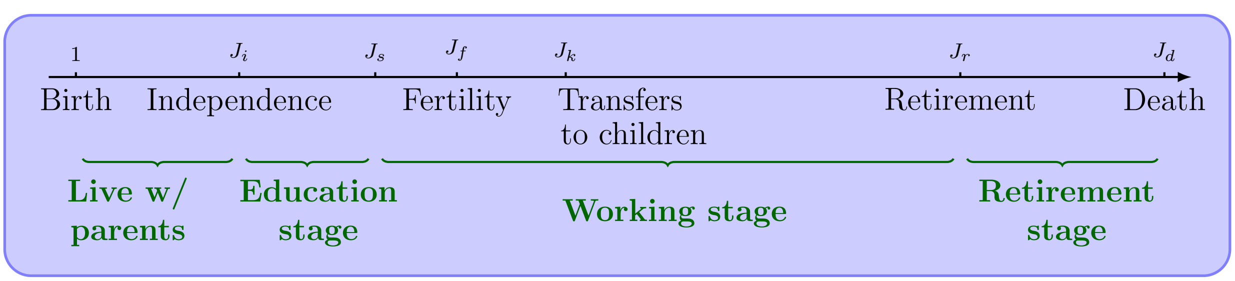
We specify a life-cycle economy in a dynastic framework with four main stages. In the first stage, individuals live with their parents. In the second stage, agents decide whether to attend school or start working. Education increases their human capital and modifies their life cycle of income, as well as the income distribution of their offspring. Once agents exit the education phase, they enter the third stage, which represents their labor market experience. Idiosyncratic uninsurable income risk makes individual earnings stochastic. Throughout their lives, agents choose savings and consumption expenditures. They can borrow only up to a limit and save through a non-state-contingent asset. During this stage, they also choose how many children to have and how much of their resources to transfer to them. The last stage is retirement. At this time, agents have two sources of income: savings and retirement benefits. We study the partial equilibrium version of this economy (i.e., prices and government policies are exogenous).

The model incorporates five sources of intergenerational persistence. The following two of these five sources are endogenous and are the main focus of this paper: the choices of (i) number of children and (ii) parent-to-child transfers, both of which affect the resources available for each child's education and, hence, their labor income. In addition, the model includes the following three sources of exogenous persistence: (iii) the initial human capital (i.e., at age 14 in the calibrated model) is related to parental human capital and directly affects income; (iv) the school taste is related to parental education and affects education choices; and (v) adult income shocks, which reduce the importance of initial conditions for labor earnings. In Section 4 we will study the importance of each of these forces for education, inequality, and intergenerational mobility.

## 2.1 The individual problem

Figure 4 shows the life cycle of an agent, in which each period in the model refers to two years. Let $j$ denote age at the beginning of the period. From $j = 1$ until $j = J_i$, the child lives with her parents, who choose the child's consumption. At age $j = J_i$, the child becomes independent. Her initial states are assets, human capital, and school taste (or psychic cost). Initial assets are money transfers from her parents. The initial human capital and school taste are stochastic but correlated with the parents' education and human capital.

Figure 4: **Life cycle**




Agents can only trade risk-free bonds, but interest rates are different for saving and borrowing. Agents with positive savings receive an interest rate equal to $r$, while those borrowing pay an interest rate equal to $r^- = r + \iota$, where $\iota \geq 0$. The wedge between interest rates is important to capture the cost of borrowing, which is a form of insurance relevant for the quantitative analysis. Individuals face borrowing limits that vary over the life cycle. Young workers (i.e., under the age of $J_s$) and retired households cannot borrow. Student loans are explained in detail below. Let $e \in \{1, 2, 3\}$ be the current level of education of the agent, which stands for high-school dropout, high-school graduate, and college graduate, respectively. Workers with access to borrowing (i.e., after age $J_s$) are subject to credit limit of $\underline{a}(e)$. Estimates of $\underline{a}(e)$ are based on self-reported limits on unsecured credit from the Survey of Consumer Finances.

**Education stage:** From $j = J_i$ until $j = J_s$, the agent has the option to study. The individual state variables are assets $a$, human capital $h$, and school taste $\phi$. The first choice the agent makes is the education decision, which is irreversible. All agents become independent as high school dropouts ($e = 1$). The agent can choose to become a high-school graduate ($e = 2$), which takes 2 periods (4 years) or a college graduate ($e = 3$), which takes 4 periods (8 years). If an agent chooses to stay in school, her human capital evolves deterministically as $f^s_{\Omega(j)}(h)$, where $\Omega(j) \in \{HS, Coll\}$ is either high-school or college depending on the age $j$ of the agent.

The price of education is $p_{\Omega(j)}$, but, as is common in the literature (e.g., Heckman et al., 2006; Abbott et al., Forthcoming), we also allow for school taste $\phi \in [0, 1]$ to affect the total cost of education. Modeling school taste is necessary because resources available to finance schooling and returns to education can only partially account for the observed education patterns. Particularly, we assume that the school taste enters as a separate term in the value function. We scale the school taste $\phi$ by a different constant in each schooling level $\bar{\psi}_e$. After leaving school, the psychic cost is assumed not to affect any adult outcome. While working, human capital evolves stochastically and is distributed by $f^w_{e,j}(h)$. We allow for education- and age-dependent idiosyncratic labor-income shocks. In Section 3, we discuss the estimation of the returns of education and the income process.

Students face borrowing limits $\underline{a}^s_e$ for subsidized loans. High-school students cannot borrow (i.e., $\underline{a}^s_{HS} = 0$). College students have access to subsidized loans at rate $r^s = r + \iota^s$, where $\iota^s < \iota$. To simplify computation, we assume that college student debt is refinanced into a single bond that carries interest rate $r^{-}$. We assume that fixed payments would have been made for 10 periods (i.e., 20 years) following graduation, so we can transform college loans into regular bonds using the following formula:

$$\tilde{a}^{s}(a') = a' \times \frac{r^{s}}{1-(1+r^{s})^{-10}} \times \frac{1-(1+r^{-})^{-10}}{r^{-}},$$

where $\tilde{a}^{s}(a')$ is the function performing this transformation. Borrowing limit $\underline{a}_{2}^{s}$ and wedge $\iota^{s}$ will be based on federal college loans, to be explained in detail in Section 3.

Formally, let $V_{j}^{s}$ and $V_{j}^{w}$ be the value of an agent of age $j$ in school and working, respectively. The first choice the agent makes, at age $j = J_i$, is how much education to acquire. The value function at this stage is given by $V_{J_i}$

$$V_{J_i}(a,h,\phi) = \max\left\{V_{j}^{w}(a,h,1), V_{j}^{s}(a,h,2) - \phi\bar{\psi}_2, V_{j}^{s}(a,h,3) - \phi\bar{\psi}_3\right\},$$

where $V_{j}^{s}$ is defined by

$$\begin{aligned}
V_{j}^{s}(a,h,e) &= \max_{c,a'} u(c) + \beta\tilde{V}_{j+1}^{s}(\tilde{a}^{s}(a'),h',e) \qquad (3)\\
& c + a' + p_{\Omega(j)} - hw_{\Omega(j)}(1-\tau) = \begin{cases} a(1+r) & \text{if } a \geq 0 \\ a(1+r^{s}) & \text{if } a < 0 \end{cases}\\
& a' \geq \underline{a}_{\Omega(j)}^{s}, \quad h' = f_{\Omega(j)}^{s}(h)\\
& \Omega(j) = \begin{cases} HS & \text{if } j \leq J_i + 1 \text{ (i.e., high-school age)} \\ Coll & \text{if } j > J_i + 1 \text{ (i.e., college age)} \end{cases}\\
& \tilde{V}_{j+1}^{s} = \begin{cases} V_{j+1}^{w} & \text{if } e = 2 \text{ and } j = J_i + 1 \\ & \text{(i.e., last period of schooling for HS grads)} \\ V_{j+1}^{w} & \text{if } e = 3 \text{ and } j = J_i + 3 \\ & \text{(i.e., last period of schooling for college grads)} \\ V_{j+1}^{s} & \text{otherwise} \end{cases}
\end{aligned}$$

The agent is risk averse and her preferences are represented by an increasing, concave, and positive utility function $u$.[9] She can borrow up to the limit $\underline{a}^s_{\Omega(j)}$, and the return on positive savings is $1+r$. However, if the agent is borrowing, she pays interest rates $r^s > r$. Future is discounted by $\beta$. We denote as $w_{\Omega(j)}$ the wage for an agent who is currently in school at level $\Omega(j)$. In particular, we assume that the agent does not work during high school (i.e., $w_{HS} = 0$), and we allow for (part-time or internship) work while in college (i.e., $w_{Coll} \in [0, w]$).

The value of work $V^w_j$ is defined by

$$V_j^w(a,h,e) = \max_{c,a'} u(c) + \beta \mathbb{E}\left[V^w_{j+1}(a',h',e)\right], \tag{4}$$

$$c + a' - hw(1-\tau) = \begin{cases} a(1+r) & \text{if } a \geq 0 \\ a(1+r^-) & \text{if } a < 0 \end{cases}$$

$$a' \geq \underline{a}_{e,j}, \quad h' \sim f^w_{e,j}(h).$$

The agent can borrow up to the limit $\underline{a}_{e,j}$, and the return on positive savings is $1+r$. However, if the agent is borrowing she pays interest rates $r^- > r$. The return from working is the wage $w$ net of taxes $\tau$. There is no disutility from working, and so the labor supply is inelastic.

**Working stage:** From $j = J_s$ until $j = J_r$, the agent works and her individual problem is equivalent to (4). In the (exogenously given) fertility period $j = J_f$, however, the agent also chooses the number of children. Once the children become independent (at $j = J_k$), the agent also chooses the transfer to her offspring.

**Fertility:** We model altruism à la Barro and Becker (1989), in which parents care about the utility of their children. The problem at the age of fertility $j = J_f$ is

$$V_j(a,h,e) = \max_{c,c_k,a',n} u(c) + \beta \mathbb{E}\left[V_{j+1}(a',h',e,n)\right] + b(n)u(c_k) \tag{5}$$

[9]The fact that the utility function $u$ is positive is necessary to model altruism. As shown by Jones and Schoonbroodt (2010), the implicit assumption that parents enjoy having children requires that the utility function must be always positive or always negative. If we choose the negative case, we need an extra assumption for the value of having zero children. Therefore, we follow the classic approach of $u$ being always positive and assume that having zero children delivers zero utility.

$$
\begin{aligned}
& c + nc_k + a' + C(h,n) - hw(1-\tau) = \begin{cases} a(1+r) & \text{if } a \geq 0 \\ a(1+r^-) & \text{if } a < 0 \end{cases} \\
& a' \geq \underline{a}_{e,j}, \quad h' \sim f^w_{e,j}(h), \quad n \in \left\{0, 1, \ldots, \overline{N}\right\}.
\end{aligned}
$$

In this period, the agent chooses her consumption $c$, her children's consumption $c_k$, savings $a'$, and the number of children $n$, which is a discrete choice. As usual, the agent derives utility from her own consumption and her continuation utility. Furthermore, similar to Roys and Seshadri (2014), the agent is altruistic and derives utility from her children's consumption. The altruistic discount factor $b(n)$ is positive, increasing, and concave.

Raising children is costly, as is reflected in (5). Parents pay the cost $C(h, n)$ in addition to the money spent on children's consumption and transfers. This cost is assumed to be increasing in the number of children $n$ and in the level of human capital of the parents $h$. The fact that $C$ is increasing in $h$ will be essential to obtain the fertility differentials described in Section 1. Its functional form and estimation are described in Section 3.

Until the agent's children become independent ($j = J_k$), she chooses the children's consumption and pays the cost $C$. Hence, the problem is equal to (5) but takes the number of children $n$ as given. The transfer to each child $\varphi$ is assumed to be made in the period before the offspring become independent (age $j = J_k$). Moreover, transfers are assumed to be the same for all children.[10] The problem at the age when transfer to children is chosen $j = J_k$ is

$$
\begin{aligned}
V_j(a,h,e,n) = \max_{c, c_k, a', \varphi} u(c) + \beta \mathbb{E}\left[V_{j+1}(a',h',e)\right] + b(n)\left\{u(c_k) + \beta \mathbb{E}\left[V_{J_i}(\varphi, h_k, \phi_k)\right]\right\} \qquad (6) \\
c + nc_k + a' + \frac{n\varphi}{(1+r)} + C(h,n) - hw(1-\tau) = \begin{cases} a(1+r) & \text{if } a \geq 0 \\ a(1+r^-) & \text{if } a < 0 \end{cases} \\
a' \geq \underline{a}_{e,j}, \quad h' \sim f^w_{e,j}(h), \quad h_k \sim f^k(h), \quad \phi_k \sim g^k(e)
\end{aligned}
$$

Notice that unlike (5), the value function at this stage now includes the continuation value of the

[10] The altruism value derived from children depends on their initial assets. We assume that (one period in advance) parents set a fund for their children to receive $\varphi$ when they become independent.

children $V_{J_i}$. This is the last period in which parents' choices affect their descendants. As the problem is written recursively, this implies that at every period in which parents' choices affect children's outcomes, the value function of their descendants will be taken into account. This embeds the parental altruism motives. The initial human capital and the school taste of the children are stochastic but correlated with the parents' human capital and level of education, respectively. The functional form of the altruism, as well at the stochastic processes of human capital, $f^k(h)$, and psychic costs, $g^k(e)$, are specified in Section 3.

**Retirement stage:** At $j = J_r$, the agent retires with two sources of income: savings and retirement benefits. These benefits depend on her education level and human capital and are progressive. Formally, the problem at the age of retirement is

$$\begin{aligned} V_j\left(a,h,e\right) = \max_{c,a'} u\left(c\right) + \beta V^w_{j+1}\left(a',h,e\right), \\ c + a' = \pi(e,h) + a\left(1+r\right), \\ a' \geq 0, \end{aligned} \tag{7}$$

where $\pi$ are the retirement benefits, which depend on the education and human capital at the age of retirement.[11]

# 3 Estimation

The model is estimated to match household level data so an agent in the model corresponds to a household with two adults in the data. The number of children $n$ is also in terms of households—i.e., $n = 1$ refers to one household.[12] We use the following three primary data sources: (i) IPUMS US Census; (ii) CPS Fertility Supplement; and (iii) 1979 cohort of the National Longitudinal Survey of Youth (NLSY79). We select a population for which our model can be taken as a reasonable approximation to household behavior and impose two selection

[11]We use education, together with the last level of human capital, as a proxy to approximate average lifetime income with which the retirement benefits are determined. See Section 3 for details.

[12]We set the maximum possible number of children to 6, so $\overline{N} = 3$.

criteria on the data. First, as is standard in the literature (e.g., Huggett et al., 2011), we drop household observations with income below a certain threshold. We choose this threshold as the one that corresponds to one person working 20 hours a week for the minimum wage (approximately $8,000 total annual household income). Second, there is no decision regarding marriage in our model. Given our focus on fertility, we are interested in two-member households. To avoid differences in income and time availability due to single parenthood, we keep only married households. Details about sample selection are reported in Appendix B.1.

Table 3: **Externally estimated parameters**.

| Parameter | Value | Description | Source |
|---|---|---|---|
| **Demographics** | | | |
| | 2 | Time period | |
| $J_i$ | 14 | Independent | |
| $J_s$ | 22 | Maximum age for education | |
| $J_f$ | 28 | Fertility decisions | |
| $J_k$ | 36 | Transfers to children | |
| $J_r$ | 68 | Retirement | |
| $J_d$ | 80 | Death | |
| **Prices** | | | |
| $\bar{y}_{40}^{HS} = w \times \bar{h}_{40}^{HS}$ | $w = 1$, $\bar{h}_{40}^{HS} = 1$ | Average Income: HS Graduate, Age 40-41 | Normalization |
| $w_{Coll}$ | 0.56 | Wage while in college | Census |
| $\tau$ | 12.4% | Payroll tax | Social Security |
| $p_{HS}$ | 0.05 | Price of high school | Digest of Education Statistics |
| $p_{Coll}$ | 0.58 | Price of college | Delta Cost Project |
| **Financial markets** | | | |
| $r$ | 3% | Interest rate (annual) | Smets and Wouters (2007) |
| $\underline{a}_1$ | -10 | Borrowing limit of HS dropout ($1k) | SCF |
| $\underline{a}_2$ | -24 | Borrowing limit of HS graduate ($1k) | SCF |
| $\underline{a}_3$ | -34 | Borrowing limit of college graduate ($1k) | SCF |
| $\iota$ | 10% | Borrowing-saving wedge (annual) | Gross and Souleles (2002) |
| $\iota^s$ | 1% | College loan wedge (annual) | NCES |
| **Income process** | | | |
| *Estimated to match mean and variance growth by age and education. See text and Figure 5.* | | | Census |
| **Childcare** | | | |
| $c_3$ | 0.64 | Returns to scale | Folbre (2008) |
| **Preferences** | | | |
| $\beta$ | 0.975 | Discount factor (annual) | |
| $\gamma_c$ | 0.5 | Risk aversion | Roys and Seshadri (2014) |

*Note: Prices are normalized using the average income of a high school graduate at age 40, $\bar{y}_{40}^{HS}$ = \$60,198, based on IPUMS. SCF refers to the 2001 Survey of Consumer Finances. NCES refers to the report "Student Financing of Undergraduate Education: 1999-2000," from the National Center for Education Statistics. Census refers to the 2000 Census data (IPUMS).*

We numerically solve the steady state of this economy. There are several non-convexities due to the discrete choices in education and fertility, so we apply a global solution method.[13] We then compute the ergodic distribution of the economy to match moments from the US in 2000.

[13] We adapt the generalized endogenous grid method proposed by Fella (2014).

We describe below how we parameterize the model economy. Some of the parameters can be estimated "externally," while others must be estimated "internally" from the simulation of the model. Table 3 reports all externally calibrated parameters, while Table 4 summarizes all the internally estimated parameters in the model, as well as the moments used to estimate them. Although the model is highly nonlinear, so that all parameters potentially affect all outcomes, the estimation of some parameters relies on some key moments in the data. We briefly discuss this relation between parameters and moments in this section.

### 3.1 Simulated Method of Moments

**Demographics:** A period in the model is two years. Individuals become independent at the age of $J_i = 14$, and they start with the equivalent of 7 years of education. They can go to high school (two periods) and then to college (another two periods), and so the maximum age for education is $J_s = 22$. Fertility decisions are made around the average age at first birth, $J_f = 28$. At age $J_k = 40$, one period before the agent's children become independent, she chooses the assets to transfer to her children. Retirement occurs at $J_r = 68$. Death is assumed to occur for all agents at age $J_d = 80$.

**Prices:** Prices are normalized such that the average income of a high school graduate at age 40 is equal to $\$60,198$, as in the data. We estimate the wage while in college from IPUMS census data. We focus on individuals between the ages of 18 and 22 years and match the relative earnings of those currently in college relative to those who are not, leading to $w_{Coll} = 0.56$. We set the annual interest rate to $r = 3\%$ (e.g. Smets and Wouters, 2007).[14] Based on self-reported limits on unsecured credit by family from the Survey of Consumer Finances, we set $\underline{a}_{e,j}$, the borrowing limits for working-age ($J_s < j < J_r$) individuals, to $\{-10,000, -24,000, -34,000\}$ for high school dropout, high school graduate, and college graduate, respectively. The (annualized) wedge $\iota$ for borrowing is set to 10% which is the average among the values for credit card borrowing interest rates (net of $r$ and average inflation) reported by Gross and Souleles (2002).[15]

[14]The estimated model is associated with a capital-output (annualized) ratio of 3.3, similar to the standard estimate of 3.

[15]Gross and Souleles (2002) reports an average credit card interest rate of 17% between 1995 and 1998.

The yearly price of college is from the Delta Cost Project, where we get $\$6,588$.[16] The yearly price of high school is obtained from the Digest of Education Statistics, using the relative private cost of high school to college. Our estimate of high school cost is about 9% of college cost, which is consistent with the US education system (i.e., relatively low cost of high school when compared to college), leading to a price for high school of $593. Taking into account that education takes two periods (4 years) and households contain two members, our normalization leads to $p_{HS} = 0.05$ and $p_{Coll} = 0.58$.

**College Loans:** College students have access to subsidized loans at rate $r^s = r + \iota^s$. According to the National Center for Education Statistics report "Student Financing of Undergraduate Education: 1999-2000," among the undergraduates who borrow, nearly all (97%) took out federal student loans—only 13% took out nonfederal loans. Moreover, the average loan value was similar for both federal and nonfederal cases. Since average values were similar but federal loans were significantly more common, we focus on federal loans for our model estimation. Among federal loans, the Stafford loan program was the most common: 96% of the undergraduates who borrowed took out Stafford loans. The second most common loans were the Perkins loans, but they were much smaller: Only 11% of borrowers used Perkins loans, and average amounts were one quarter of average Stafford amounts. Therefore, we focus particularly on Stafford loans. Stafford offers multiple types of loans, so we use the weighted average interest rate to set $\iota^s = 0.009$. The borrowing limit while in college in the model is the set to match the cumulative borrowing limit on Stafford loans ($23,000).

**School Taste:** In this class of models, it is difficult to match the high school dropout rate. Previous studies (e.g., Abbott et al., Forthcoming; Krueger and Ludwig, 2016) introduced nonpecuniary (psychic) costs of education. We assume the agent's school taste (or psychic cost) $\phi$ is between 0 and 1, which will be scaled by different estimated levels according to the education stage ($\bar{\psi}_2$ and $\bar{\psi}_3$). Its distribution is related to parents' education through

During this period the average federal funds rate plus inflation was approximately 7%, so we choose $\iota$ such that the annualized wedge is 10%.

[16] We take into account grants and scholarships, such that only private tuition costs are considered. Prices are in 2000 US dollars.

the parameter $\omega$. Particularly, we assume that the psychic cost for children of high-school-graduate parents is uniformly distributed in that range. On the other hand, we assume that the probability of high psychic costs for children of high school dropouts is increasing in $\omega$, and decreasing for those of college graduates. Hence, the CDF of school taste is

$$G^k(e,\phi) = \begin{cases} \phi^\omega & \text{if parents are high school dropouts} \\ \phi & \text{if parents are high school graduates} \\ 1-(1-\phi)^\omega & \text{if parents are college graduates.} \end{cases} \tag{8}$$

The share of high-school and college graduates will be particularly informative $\bar{\psi}_2$ and $\bar{\psi}_3$. For larger values of high school's (college's) taste shocks, we would observe more high school dropouts (less college graduates). In addition, higher correlation between parents' education and child's school taste implies lower intergenerational mobility of education. We target the trace index of education mobility equivalent to $(3-\text{trace}(P))/2$ where $P$ is the transition matrix of education. Hence, zero mobility would imply an index equal to zero while perfect mobility implies an index equal to one. Thus, the degree of intergenerational mobility of education observed in the data will be informative about $\omega$. Our estimation suggests that psychic costs are higher for children of less-educated parents, which is consistent with previous estimates in the literature.

**Education returns:** Returns to education are allowed to vary between high school and college as well as between agents, as suggested by Heckman et al. (2006). Particularly, we specify the human-capital production function to have the nonlinear form

$$f^s_{\Omega(j)}(h) \equiv h + \alpha_{\Omega(j)} h^{\beta_{\Omega(j)}} \tag{9}$$

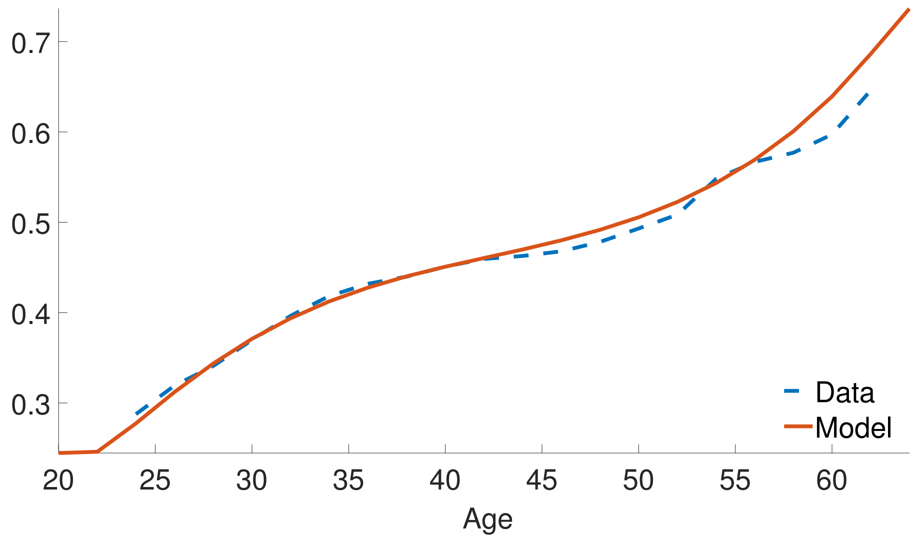
for $\Omega(j) \in \{HS, Coll\}$. Income ratios between education groups are informative about the levels of education returns $\alpha_{\Omega(j)}$, while the variance of log-income of agents with different education levels are informative about the curvature parameters $\beta_{\Omega(j)}$. In particular, a higher curvature implies a larger variation of income. Table 4 shows that our estimates for high school are $\alpha_{HS} = 0.18$ and $\beta_{HS} = 0.61$, while for college they are $\alpha_{Coll} = 0.20$ and $\beta_{Coll} = 0.72$. If we estimated the return to education at age 40-41, our model would suggest average yearly returns (in the whole population, not just those that attend school) of 12%. On the other hand, if we estimated the returns using lifetime earnings and taking into account education costs, the returns would be reduced to an average of 9% per year. These numbers are in line with empirical estimates in the literature summarized in Heckman et al. (2006).

**Labor-income risk:** We assume that $h' = f^w_{e,j}(h) \equiv h(1+\delta)$, where $\delta$ is stochastic and can take three values that vary by age $j$ and education $e$. Together with their probabilities, they are calibrated using the Rouwenhorst method to match the first difference of mean and variance of log earnings between the ages of 24 and 63, by education.[17] Two comments are appropriate. First, income risk is calibrated to include total earnings variation, encompassing what may be considered both wage shocks and hours-worked (or effort) differences. Second, even though we propose a simple model of income, we are able to match standard statistics of labor earnings. This is necessary to properly evaluate the impact of initial opportunities on income inequality. Otherwise, the comparison could be favorable for initial opportunities. Figure 5 shows that the variance of log income is well estimated, though slightly higher for older ages. Moreover, in Table 5 we will show that the persistence of the income process is correctly fitted.

**Opportunity cost of children:** The functional form assumed is $C(h,n) = c_1 h^{c_2} w(1-\tau) n^{c_3}$. This function allows for non-constant returns to scale in the number of children. Moreover, parameter $c_2$ allows for non-linearity in $h$, which helps us capture the fertility by income deciles. We estimate the returns to scale $c_3 = 0.65$, based on Table 6.4 in Folbre (2009). The estimated values of $c_1$ and $c_2$ will be informed by the fertility rates by income deciles. As the opportunity cost of having children increases (i.e., higher $c_1$), it becomes more costly to raise children, which implies a decreasing mean fertility rate. A lower value of $c_2$ implies that costs do not increase as much for higher-income parents. Thus, the rate of decay of the fertility by income will be particularly informative for $c_2$. We estimate $c_1 = 0.66$ and $c_2 = 0.59$. This can be interpreted as some child expenses being fixed costs or as higher-income parents using market services (e.g., nannies or extra-curricular programs), which reduce the amount of total (i.e., not necessarily

[17] We assume that the income-shocks distribution is constant before 24 and after 63 years of age, as data are problematic for those ages.

Figure 5: **Variance of Log(income) by age**.




*Source: Census. The model is simulated at the estimated parameters, and the variance of log(income) is computed for each age.*

quality) time they need to spend with their children.

**Replacement benefits:** The pension replacement rate is based on the Old Age, Survivors, and Disability Insurance federal program. The payroll tax is $\tau = 0.124$, which is the current rate for Social Security. We then use education level, as well as the level of human capital at the moment of retirement, to estimate the average lifetime income, on which the replacement benefit is based. See Appendix B.2 for details.

**Intergenerational transmission of human capital:** We assume that the initial (i.e., at age $J_i$) level of human capital is stochastic but correlated with the parents' human capital. The initial draw of human capital will be given by

$$log(h_{J_i}) = log(\bar{h}) + \rho \left[ log(h_p) - log(\bar{h}) \right] + \varepsilon, \tag{10}$$

where $\varepsilon \sim N(-0.5\sigma^2_{h0}, \sigma_{h0})$ and $\bar{h}$ is the average human capital in the economy.[18] This defines $f^k$, the distribution of the initial draw of human capital in the household problem (6). The variance of log-income of high school dropouts in the model is positively related to the vari-

[18]Recall that the mean of this distribution is chosen such that the average labor income of a high school graduate at age 40 is normalized to one.

ance of the initial draw of human capital. As the initial draw becomes more dispersed, this variance increases.[19] The degree of intergenerational mobility of income observed in the data is informative about $\rho$: A higher persistence in the initial draw leads to a lower intergenerational mobility of income (higher rank-rank coefficient).

**Preferences:** We specify the period utility over consumption as a CRRA function

$$u(c) = \frac{c^{1-\gamma_c}}{1-\gamma_c}.$$

As discussed in Section 2, the utility function has to be positive, and therefore $\gamma_c \in [0, 1)$. We follow the literature and assume that $\gamma_c = 0.5$ (e.g., Roys and Seshadri, 2014). Other articles, like Manuelli and Seshadri (2009), that have estimated this parameter also obtain roughly this value. As is standard in the literature, the altruism function is assumed to be $b(n) = \lambda_n n^{\gamma_n}$. The target moment of average transfers from parents to children (as a share of average income) will be informative about $\lambda_n$ since parents that value their children more (i.e., higher $\lambda_n$), would increase the transfers to them. The curvature of altruism ($\gamma_n$) will be informed by the fertility rate of different income deciles. When $\gamma_n = 0$, the marginal value of an additional child is equal to zero, which implies that all parents have (at most) one child. When $\gamma_n$ is positive, however, the quantity-quality trade-off can generate a negative fertility elasticity.

To summarize, thirteen parameters of the model are estimated using Simulated Method of Moments with 20 target moments. Two parameters, $\lambda_n$ and $\gamma_n$, are related to altruism; $\sigma_{h_0}$ is the standard deviation of the initial distribution of human capital; $\rho$ relates to the intergenerational persistence of human capital through the initial draw; $c_1$ and $c_2$ are the opportunity cost of raising children; $\alpha_{\Omega(j)}$ and $\beta_{\Omega(j)}$, for $\Omega(j) \in \{HS, Coll\}$, define the returns to education in high school and college; $\bar{\psi}_e$, for $e \in \{2, 3\}$, defines the distribution (both mean and standard deviation) of the school taste; and $\omega$ is related to the correlation of this school taste and parents' education level.

[19] We highlight here the role of high-school dropouts since other education groups go through changes in human capital, given by $f^s$, that can affect the dispersion of human capital. We, however, also target the variance of log-income for these other education groups.

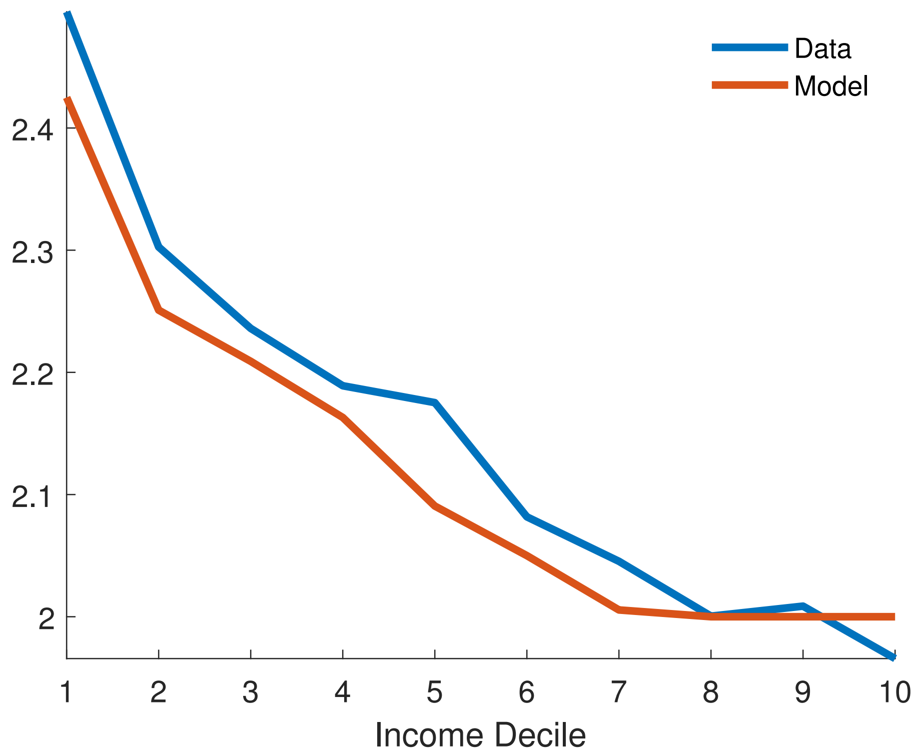
Table 4: **Internally estimated parameters**.

| Parameter | Value | Description | Moment | Data | Model |
|---|---|---|---|---|---|
| **Altruism** | | | | | |
| $\lambda$ | 0.57 | Level | Parent-to-Child Transfers | 0.43 | 0.42 |
| $\gamma$ | 0.26 | Curvature | Fertility by income deciles | | |
| **Child cost** | | | | | |
| $c_1$ | 0.66 | Level | Fertility by income deciles | | |
| $c_2$ | 0.59 | Curvature | Fertility by income deciles | | |
| **Initial draw of human capital** | | | | | |
| $\rho$ | 0.20 | Intergenerational persistence | Intergenerational mobility of income: Rank-Rank | 0.29 | 0.28 |
| $\sigma_{h_0}$ | 0.48 | Standard deviation | Variance of log(income): HS dropout 28-29 | 0.32 | 0.34 |
| **Education returns** | | | | | |
| $\alpha_{HS}$ | 0.18 | High School: level | Log(Income) Ratio Age 40-41: HS Dropout - HS Grad | -0.48 | -0.50 |
| $\alpha_{Coll}$ | 0.20 | College: level | Log(Income) Ratio Age 40-41: College Grad - HS Grad | 0.53 | 0.57 |
| $\beta_{HS}$ | 0.61 | High School: curvature | Variance of log(income): HS Grad 28-29 | 0.27 | 0.25 |
| $\beta_{Colls}$ | 0.72 | College: curvature | Variance of log(income): College Grad 28-29 | 0.26 | 0.26 |
| **School taste** | | | | | |
| $\bar{\Phi}_2$ | 5.52 | High School | High School Dropout (%) | 0.09 | 0.10 |
| $\bar{\Phi}_3$ | 37.29 | College | College Graduates (%) | 0.31 | 0.29 |
| $\omega$ | 1.80 | Intergenerational correlation | Intergenerational mobility of education | 0.85 | 0.84 |

*Source: Education shares, income ratios, variances of log(income), and fertility by income deciles are calculated from 2000 Census data (IPUMS). Parent-to-Child transfers refers to the average transfer (as a share of mean income) from Abbott et al. (Forthcoming). Intergenerational mobility of education is measured using the trace index, as reported by Checchi et al. (1999). Intergenerational mobility of income is measured using the rank-rank coefficient reported by Chetty et. al. (2014) for children of married parents.*

Table 4 shows the estimated parameters and target moments in the simulated economy. Figure 6 shows the moments regarding fertility by income deciles. Parent-to-children transfers (average), as well as fertility rates, are successfully matched, which is necessary given their key roles in our model. As for income inequality, the model displays levels similar to the data. Education shares are well matched in the model. We also obtain levels of intergenerational mobility that are close to the empirical evidence.

Figure 6: **Fertility by Income Deciles: Model and Data**.




*Note: The model is estimated to replicate the fertility rate by income deciles from the 2000 Census.*

## 3.2 Validation Exercises

We can test the validity of our estimated model by looking at moments that are not directly targeted. First, we evaluate the model within the steady state given by the estimated parameters in Tables 3 and 4. Next, we test how the model compares with the cross-state evidence reported in Section 1 by moving away from the steady state. Table 5 summarizes the results of these exercises.

First, capturing the correct persistence of income in this type of model is important, as it determines the social mobility within the working lifetime. We estimate an income process for each education group similar to Heathcote et al. (2010), but using household income and 2-year periods instead.[20] The first panel of Table 5 shows that the coefficients that determine the persistence of shocks by education level are close to 0.9 in all cases. This is in line with what we

[20]See Appendix B.3 for details.

find in the data. The estimation targeted the variance of log-income—a measure of inequality. Table 5 shows that the model is also in line with another measure of inequality; i.e., the Gini coefficient.[21]

Table 5: **Validation exercises**.

| Moment | Data | Model |
|---|---|---|
| **Income persistence** | | |
| High school dropouts | 0.92 | 0.94 |
| High school graduates | 0.92 | 0.94 |
| College graduates | 0.95 | 0.95 |
| **Inequality** | | |
| Income Gini | 0.38 | 0.39 |
| **Fertility by education** | | |
| High school dropouts | 2.90 | 2.60 |
| High school graduates | 2.16 | 2.10 |
| College graduates | 2.05 | 2.00 |
| **Fertility elasticity by education** | | |
| High school dropouts | -0.22 | -0.20 |
| High school graduates | -0.17 | -0.07 |
| College graduates | -0.08 | -0.00 |
| **Cross-State Evidence: Regression Coefficients** | | |
| Fertility rate to avg. income | -0.40 | -0.32 |
| Fertility elasticity to avg. income | 0.23 | 0.15 |
| High-school graduation rate to fertility elasticity | 0.07 | 0.30 |

*Source: For the income-persistence estimates, we follow Heathcote et al. (2010). Regression coefficients in the data are shown in Tables A.2, 1, and 2.*

Next, we evaluate fertility decisions within different education groups. First, the average fertility rate is decreasing with education both in the model and in the data. Second, the model generates fertility elasticities to income equal to $-0.20$, $-0.07$, and 0 for high school dropouts, high school graduates, and college graduates, respectively. Both model and data display a decreasing (in absolute terms) relation with education, though the model displays a faster decreasing relation.

**Cross-state:** We do a simple exercise to show that the model is qualitatively consistent with

[21] Other measures of inequality, such as the coefficient of variation or the top-bottom, are also similar in the estimated model and the data.

the cross-state patterns described in Section 1. Recall that in the benchmark calibration, the wage was normalized to one. Consequently, to generate economies with different levels of average household income, as in the data, we move wages such that the real wage (i.e., in consumption terms) is the main change. The size of wage movements is such that average income in the simulations is in the range of the corresponding empirical estimates. Many other things beyond income vary across states and time, so the main focus of this exercise is on the qualitative (rather than quantitative) features of the model.

Note that this involves moving the model away from the steady state to which it was estimated. We also have to adjust the school taste shocks since they enter separately in the utility function and do not scale with income. The school taste maximum values $\bar{\Phi}_2$ and $\bar{\Phi}_3$ are scaled by $w^z$. We set $z$ such that when wage $w$ is adjusted to match the differences in average income between 1960 and 1970, the average high-school dropout rate of children born between those years changes as in the data. Most of our results, however, are robust to alternative adjustments.[22] The last panel of Table 5 shows three cross-state estimations, both in the data and the model.

The first two rows in the last panel of Table 5 refer to the relation between average income and fertility. First, the model is able to capture the negative relationship between average income and the fertility rate, as estimated in Appendix Table A.2. The model generates a slope coefficient between the fertility rate and GDP per capita of $-0.32$, which is close to the empirical estimate of $-0.40$.

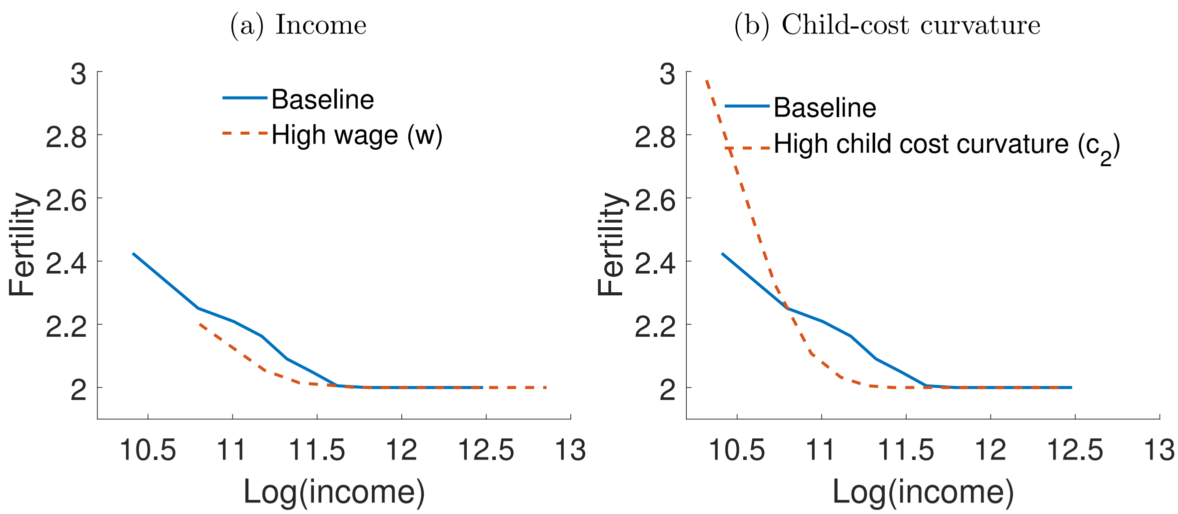
The model is also able to capture the relation between average income and fertility elasticity, as shown in Table 1. The model generates a slope coefficient of 0.15, which is similar to the data value of 0.23. Figure 7 explains the main mechanism behind this result by showing the relation between fertility and income under different economies. The left panel shows the fertility rate for different levels of income in the baseline estimation under alternative level of wages $w$. As shown in Figure 6, there is a negative relation between fertility and income with high-income households having 2 children. As the wage increases, the income distribution shifts

[22] For example, if we do not adjust school taste with wages (i.e., $z = 0$), results regarding the fertility-income and elasticity-income relations are almost unchanged.

to the right, with more individuals having the same amount of children (i.e., 2). Consequently, fertility differentials become smaller as the income distribution shifts to the right.

The curvature of the child-cost function (given by $c_2$) is the key parameter behind the elasticity, as well as the relation between the elasticity and average income. The right panel of Figure 7 shows that increasing $c_2$ leads to larger fertility differentials with high-income households still having two children. Thus, when the income distribution shifts to the right in this case, the change in fertility differential will be larger than when $c_2$ is lower (as in the baseline). For example, if $c_2$ is equal to 0.70 (as in the figure, instead of 0.59 as in the baseline) the regression coefficient between fertility elasticity and average income increases from 0.15 to 0.19.

Figure 7: **Fertility choices: income and child-cost curvature**.




*Note: The left panel shows the fertility rate for different levels of $w$ in the baseline estimation. The right panel shows how fertility changes with the curvature ($c_2$) of the child-cost function.*

The last row of Table 5 shows education outcomes and fertility differences across income groups. Table 2 presents evidence that children born in states with smaller fertility differences between income groups are associated with higher high-school graduation rates. Even though the model produces a larger effect, it is qualitatively similar to the data. We take this as evidence that the model can also capture our main patterns of interest outside of the economy on which the benchmark is estimated.

# 4 Sources of Income Inequality and Intergenerational Mobility

Initial conditions (i.e., initial human capital, school taste, and initial assets) explain 60% of the variation of lifetime earnings in the model. But, What are the forces driving the importance of initial conditions? Our estimated model allows us to study the quantitative importance of both endogenous and exogenous sources of income inequality and intergenerational persistence.

We focus on the role of two endogenous family choices: fertility and transfers. In this section we show and explain that in an economy without fertility differentials would have 7% higher intergenerational mobility and 1% lower income inequality. The impact of a counterfactual constant transfer per child is twice as large. We also study the role of three exogenous forces (shocks): initial human capital, school taste, and adult income shocks. Among these, the stochastic process behind initial human capital is the most important determinant of inequality and mobility.

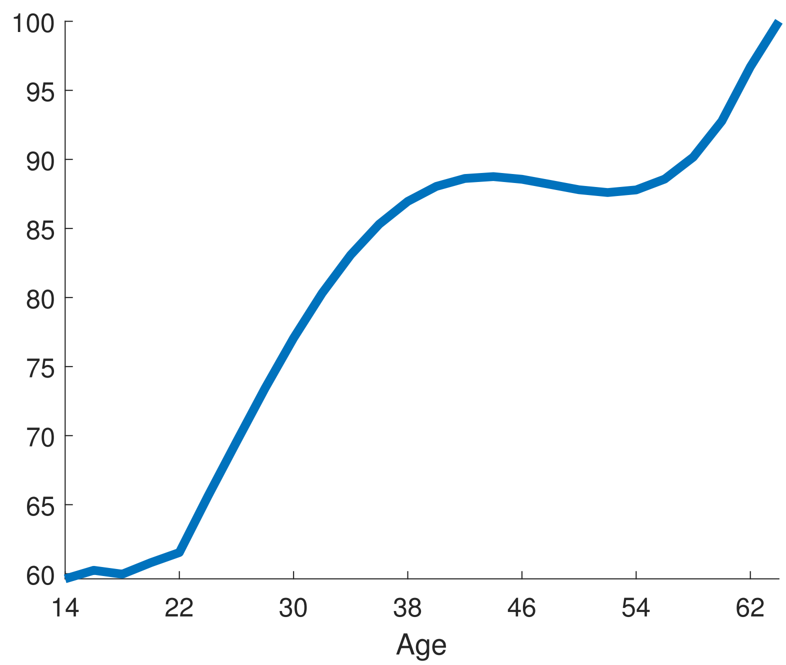
## 4.1 Variance of Lifetime Earnings

We decompose the variance of lifetime earnings into variation due to initial conditions and variation due to adult income shocks. An agent starts his life with an initial level of human capital (which is imperfectly correlated with the human capital of his parent); initial assets (which are the transfers' choice of the parent); and a school taste (which is imperfectly correlated with parent's education). Most of the lifetime earnings inequality is explained by initial conditions in our model. The coefficient of variation of lifetime earnings is 0.75, with 60% being explained by the three initial conditions (column 1 of Table 6). Among these variables, the initial human capital is the most important and explains about 46% of the variation, while school taste explains about 10% and initial assets about 5%. After the agent becomes independent, the only sources of variation are the adult income shocks, which explain the remaining 40%. Even though our model choices are different, our results are similar to Huggett et al. (2011).

Differently from them, however, we will be able to explore the role of family choices (fertility and transfers) in explaining inequality and intergenerational persistence.

We can decompose the variance of lifetime earnings for the conditions given at different ages (i.e., the state variables at older ages). To understand the decomposition, it is helpful to start at the end of the life cycle and iterate backwards. In any period, the state variables determine current labor income. However, future labor income is subject to shocks. Therefore, in the last period of work, all shocks determining labor income have been realized and current state variables explain all (100% of) future earnings. One period before, the agent knows its current labor income, but its next (and last) period's income is subject to an idiosyncratic shock. Iterating backward toward the initial period, the agent faces more uncertainty about future labor income, and as a result, the current state provides less information about future earnings. Figure 8 shows that this decomposition increases with age and converges to 100%. The main takeaway from this figure is that shocks received between ages 20 and 40 seem to be the most important to predict future income.

Figure 8: **Variance of future earnings explained by current state**.




*Note: For each age, we show the share of the variance of future earnings predicted by the current state variables.*

Table 6: **Intergenerational mobility and inequality: Endogenous forces.**

| | Benchmark | Constant fertility | Constant transfers |
|---|---|---|---|
| **Fertility and transfers** | | | |
| Mean fertility | 2.119 | 2.119 | 2.000 |
| Fertility elasticity | -0.098 | 0.000 | 0.000 |
| Mean transfer to children | 0.415 | 0.391 | 0.411 |
| CV transfers to children | 0.878 | 0.823 | 0.001 |
| **Education** | | | |
| Dropouts | 9.752 | 8.050 | 5.630 |
| High-school graduates | 60.776 | 61.221 | 63.317 |
| College graduates | 29.472 | 30.729 | 31.054 |
| **Mobility** | | | |
| Intergenerational Mobility: Rank-Rank | 0.283 | 0.264 | 0.237 |
| Transition: Parent Q1 and Child Q5 | 0.101 | 0.106 | 0.114 |
| Intergenerational Education Persistence: Trace | 0.845 | 0.868 | 0.886 |
| Bottom parents (income Q1 & high-school dropouts) | | | |
| Children's income rank | 31.453 | 31.735 | 33.097 |
| Children high-school dropouts | 30.512 | 25.301 | 13.464 |
| Children high-school graduates | 60.769 | 65.946 | 78.092 |
| Children college graduates | 8.719 | 8.754 | 8.444 |
| **Inequality** | | | |
| Variance of log Lifetime Earnings | 0.406 | 0.402 | 0.399 |
| CV of Lifetime Earnings | 0.751 | 0.746 | 0.742 |
| % expl. by all initial conditions | 60.747 | 60.234 | 59.922 |
| % expl. by human capital | 46.273 | 46.042 | 46.431 |
| % expl. by transfers | 4.507 | 4.099 | 0.000 |
| % expl. by school taste | 10.501 | 10.147 | 9.621 |
| % expl. by adult income shocks | 39.253 | 39.766 | 40.078 |
| Total | 100.000 | 100.000 | 100.000 |

*Note: In the case of constant fertility, we keep the same model and estimated parameters from Section 3 but assume fertility $n$ is exogenous and each household has 2.12 children, equal to the average fertility in the baseline model. In the case of constant transfers, we assume, instead, that parents' transfers are constant at the average value in the baseline model.*

## 4.2 Endogenous Forces: The Role of Fertility and Transfers

We start by analyzing the effects of endogenous choices of fertility and transfers on income inequality and social mobility.

**The Role of Fertility** We use our model to study the role of endogenous fertility on income inequality and intergenerational mobility. For this we keep the same model and estimated parameters from Section 3 but examine the case of constant fertility (assuming fertility $n$ is exogenous and each household has 2.12 children, equal to the average fertility in the baseline model).

In an economy with constant fertility, income inequality (measured as the variance of log lifetime earnings) would decrease by 1% (from 0.406 to 0.402, third panel of Table 6). The effect on income inequality, however, varies across the life-cycle. The solid blue line of Figure 9 shows the variance of log income by age in an economy with constant fertility relative to the benchmark with endogenous fertility. For agents between ages 20 and 50, the effects are twice as large—income inequality would decrease by 2%. As agents grow older, the effect of initial conditions (which are more affected by endogenous fertility differentials) is diluted by life-cycle income shocks. Fertility choices, thus, have a stronger effect on inequality among younger individuals.

Without fertility differentials, intergenerational mobility would increase by 7% (the rank-rank correlation reduces from 0.283 to 0.264, Table 6). This change amounts to one-third of the standard deviation in intergenerational mobility across commuting zones (Chetty et al., 2014). Effects, however, are heterogeneous for children with different family backgrounds. To understand the heterogeneous effects define $p_{ij}^{s}$ as the probability of children of parents with income quintile $i$ (at age 40) achieving income quintile $j$ (at age 28) in the economy $s$, where $s$ can refer to the baseline economy or to some counterfactual (e.g., constant fertility).[23] The left panel of Figure 10 shows how these probabilities change in the constant fertility counterfactual: $\Delta p_{ij} = p_{ij}^{\text{Constant Fertility}} - p_{ij}^{\text{Baseline}}$. For the sake of clarity, the first five bars show $\Delta p_{1j}$

[23]The age choice is the one used for the intergenerational mobility coefficient used in the estimation, as calculated by Chetty et al. (2014).

for $j = 1, ..., 5$. The next five refer to children of parents in the second income quintile ($\Delta p_{2j}$) and so on. With constant fertility, children born to bottom-income-quintile parents exhibit a one percentage point lower probability of remaining in the bottom quintile (i.e., the probability falls from 33.4% to 32.3%). Children of top-quintile parents, however, have a one percentage point larger probability of dropping to the bottom quintile (i.e., the probability increases from 8.6% to 9.5%).[24]

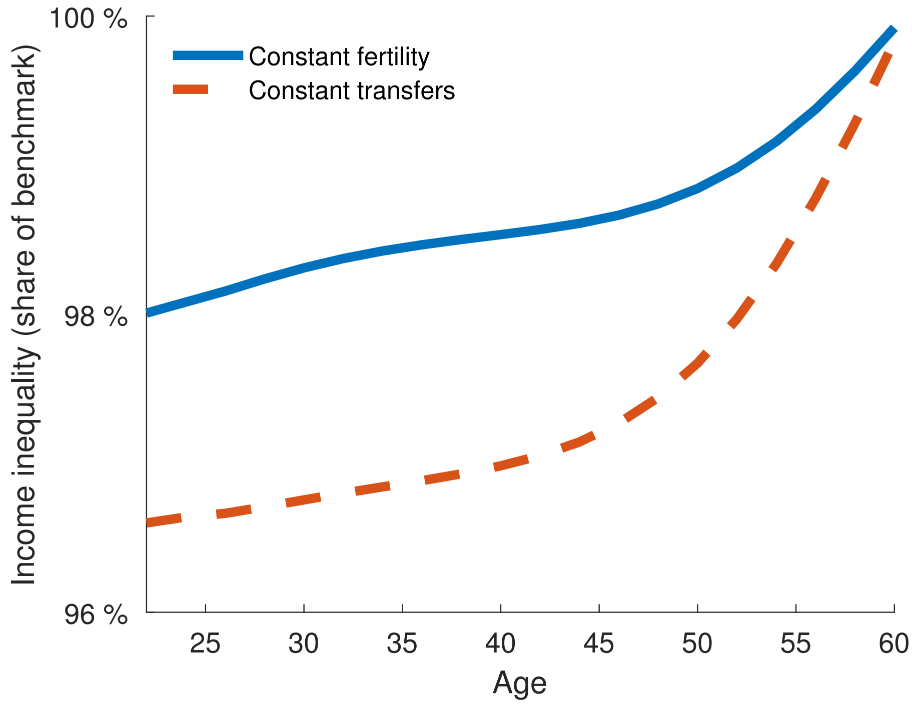
Children from low-income and low-educated parents (i.e., those of high-school dropout parents in the first income decile) are the ones with most siblings and are, therefore, the most affected by the constant fertility counterfactual. In the baseline economy, 30% of these children are high-school dropouts. When we force these families to have fewer children, parents choose to increase transfers, and the share of high-school dropouts is reduced to 25% (second panel of Table 6). Even though effects are heterogeneous, the aggregate distribution of education shifts toward an economy with fewer high school dropouts and more high school graduates, decreasing income inequality and increasing intergenerational mobility. Hence, we find that reducing the negative income-fertility profile can alleviate intergenerational poverty traps.

**The Role of Family Transfers** We evaluate an economy in which parents' transfers are exogenously constant at the average value in the baseline model. This counterfactual economy displays lower income inequality and higher social mobility. Income inequality (measured as the variance of log lifetime earnings) decreases by 2% (from 0.406 to 0.399, third panel of Table 6). Similar to the case of constant fertility, the effect on income inequality varies across the life-cycle. The dotted red line of Figure 9 shows the variance of log income by age in an economy with constant transfers relative to the benchmark with endogenous transfers. For agents between ages 20 and 50, the effects are twice as large—income inequality would decrease by almost 4%.

With constant transfers intergenerational mobility increases by 16% (from 0.283 to 0.237). This

[24]Using income ranks (rather than levels) to measure mobility implies that when one group has higher probability of achieving a certain rank, another group must have a lower probability of reaching such rank. In this case, most of the reduction in the probability of reaching the top quintile comes from children of high-income parents because this is the group that has a higher fertility rate in the counterfactual than in the baseline.

Figure 9: **Income Inequality and Family Choices**.



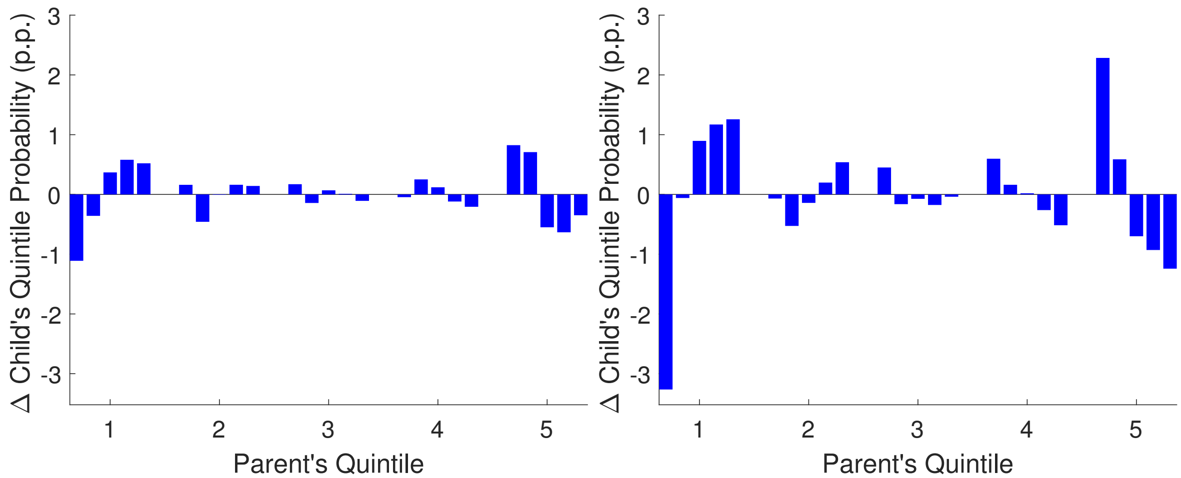

*Note: Income inequality is measured using the variance of log income. For each alternative model, we plot the resulting inequality by age as a share of the benchmark economy; i.e., 95% implies a 5% reduction in inequality.*

change amounts to approximately two-thirds of the standard deviation in intergenerational mobility across commuting zones (Chetty et al., 2014). The large role that the heterogeneity of initial assets played in education choices is eliminated, and most lifetime earnings are instead due to characteristics less directly related to parents' income. The increase in mobility is associated with a reduction in the variance of years of education, mostly driven by a decrease in the share of high-school dropouts.

Effects are also heterogeneous across children with different family backgrounds. The right panel of Figure 10 shows that children of bottom-income-quintile parents have 3 percentage points lower probability of remaining in the bottom quintile (this probability is reduced from 33.3% to 30.1%). Children of top-income-quintile parents are more likely to fall to the bottom quintile (this probability increases from 8.6% to 10.9%). Table 6 shows that effects are particularly large for children of low-income and low-educated parents (the ones with the most siblings and, hence, the lowest amount of resources per child). The high-school dropout rate for this group, for example, falls from 30.5% to 13.5%.

Figure 10: **Changes to Income Intergenerational Mobility**.

(a) Constant Fertility (b) Constant Transfers




*Note: Let $p^s_{ij}$ be the probability of children of parents with income quintile i (at age 40) achieving income quintile j (at age 28) in the economy s, where s can refer to the baseline economy or to some counterfactual (e.g., constant fertility). The age choice is the one used for the intergenerational mobility coefficient used in the estimation, as calculated by Chetty et al. (2014). The left panel shows how these probabilities change in the constant fertility counterfactual: $\Delta p_{ij} = p^{Constant\ Fertility}_{ij} - p^{Baseline}_{ij}$. For the sake of clarity, the first five bars show $\Delta p_{1j}$ for $j = 1, ..., 5$. The next five refer to children of parents in the second income quintile ($\Delta p_{2j}$). The right panel repeats the analysis for the case of constant transfers.*

## 4.3 Exogenous forces

We evaluate how income inequality and social mobility are affected by the three exogenous shocks that take place across the agent's life-cycle: initial human capital, school taste, and adult income shocks.

**Initial human capital** Columns 2–4 of Table 7 show economies under alternative scenarios for the initial human capital process described by Equation (10). We focus on three cases: *constant human capital* (all agents start with the same level of human capital regardless of the family background; i.e., $\rho = 0, \sigma_{h_0} = 0$); *i.i.d.* (the initial draw of human capital is not correlated with parents, i.e., $\rho = 0$); and *no uncertainty* (the initial draw is perfectly correlated with parents; i.e., $\sigma_{h_0} = 0$).

When the initial human capital is not correlated with the parents (either constant or i.i.d.), intergenerational mobility increases substantially. The rank-rank coefficient is reduced to 0.203 and 0.124 for the constant and i.i.d. cases, respectively. The effect on income inequality depends on the specific counterfactual. With constant initial human capital, income inequality is reduced by over 50% because there is no variation on the initial human capital. In the i.i.d. case, however, there is almost no change in inequality, because the volatility of the initial draw is the same as in the baseline economy.

When the initial human capital is not correlated with the parents, lower-income parents have more incentives to have more children since these children are more likely to be better off. Thus, mean fertility increases and fertility choices become more correlated with income (the fertility elasticity becomes more negative). This leads to lower transfers per child on average and a larger high-school-dropout rate. This result highlights that studies of human capital policies that abstract from family transfers and fertility choices may be biased in their results.

An economy in which the initial level of human capital has no uncertainty but is perfectly correlated with parents' human capital displays lower inequality but higher intergenerational persistence. Income inequality decreases by about 50%, while the rank-rank correlation increases from 0.283 to 0.354. Mean fertility is almost unchanged, while the income elasticity is twice as large. Given that $\sigma_{h_0} = 0$ but $\rho = 0.2$, human capital reverts to the average without uncertainty. Poor parents, thus, have more incentives to have children, while higher-income parents have lower incentives to do so.

**School taste** The last two columns of Table 7 evaluate alternative stochastic processes for the school taste shock as given by Equation (8). We focus on two cases: *i.i.d.* (not correlated with parents; i.e., $\omega = 1$) and *constant* (i.e., the same $\phi$ for all agents, fixed at the mean value). When the school taste is constant at the average level, all agents decide to be high-school graduates, which reduces income inequality and increases social mobility. When the school taste is i.i.d. (i.e., independent of parents' education) intergenerational mobility increases (the rank-rank correlation decreases from 0.283 to 0.247). The effects of the school taste, however,

Table 7: **Social mobility and inequality: Exogenous forces.**

| | Benchmark | Initial human capital | | | No adult | School taste | |
|---|---|---|---|---|---|---|---|
| | | constant | iid | no uncertainty | risk | iid | constant |
| **Fertility and transfers** | | | | | | | |
| Mean fertility | 2.119 | 3.234 | 2.947 | 2.124 | 2.094 | 2.359 | 2.028 |
| Fertility elasticity | -0.098 | -0.719 | -0.454 | -0.194 | -0.104 | -0.202 | -0.029 |
| Mean transfer to children | 0.415 | 0.213 | 0.312 | 0.365 | 0.406 | 0.372 | 0.453 |
| CV transfers to children | 0.878 | 1.363 | 1.371 | 0.653 | 0.784 | 1.054 | 0.782 |
| **Education** | | | | | | | |
| Dropouts | 9.752 | 34.053 | 35.574 | 7.812 | 13.048 | 21.446 | 0.000 |
| High-school graduates | 60.776 | 44.512 | 44.065 | 63.306 | 59.716 | 53.136 | 100.000 |
| College graduates | 29.472 | 21.435 | 20.361 | 28.882 | 27.236 | 25.417 | 0.000 |
| **Mobility** | | | | | | | |
| Intergenerational Mobility: Rank-Rank (100) | 0.283 | 0.203 | 0.124 | 0.354 | 0.295 | 0.247 | 0.209 |
| Transition: Parent Q1 and Child Q5 | 0.101 | 0.135 | 0.160 | 0.084 | 0.095 | 0.115 | 0.126 |
| Intergenerational Education Persistence: Trace | 0.845 | 0.794 | 0.804 | 0.821 | 0.836 | 0.970 | NaN |
| Bottom parents (income Q1 & high-school dropouts) | | | | | | | |
| Children's income rank | 31.453 | 40.011 | 43.964 | 26.689 | 31.380 | 38.960 | 38.054 |
| Children high-school dropouts | 30.512 | 56.355 | 58.406 | 29.164 | 34.709 | 27.564 | 0.004 |
| Children high-school graduates | 60.769 | 34.409 | 32.884 | 61.600 | 57.206 | 48.642 | 99.996 |
| Children college graduates | 8.719 | 9.236 | 8.710 | 9.236 | 8.085 | 23.794 | 0.000 |
| **Inequality** | | | | | | | |
| Variance of log Lifetime Earnings | 0.406 | 0.181 | 0.401 | 0.191 | 0.279 | 0.412 | 0.300 |
| CV of Lifetime Earnings | 0.751 | 0.513 | 0.751 | 0.511 | 0.567 | 0.759 | 0.610 |
| % expl. by all initial conditions | 60.747 | 36.653 | 63.636 | 32.160 | 100.000 | 62.424 | 64.813 |
| % expl. by human capital | 46.273 | 0.000 | 43.657 | 6.995 | 78.517 | 44.941 | 64.604 |
| % expl. by transfers | 4.507 | 3.384 | 1.223 | 6.858 | 6.424 | 3.018 | 2.787 |
| % expl. by school taste | 10.501 | 30.197 | 12.757 | 23.228 | 15.671 | 10.989 | 0.000 |
| % expl. by adult income shocks | 39.253 | 63.347 | 36.364 | 67.840 | 0.000 | 37.576 | 35.187 |
| Total | 100.000 | 100.000 | 100.000 | 100.000 | 100.000 | 100.000 | 100.000 |

*Note: We evaluate how income inequality and social mobility are affected by the three exogenous shocks that take place across the agent's life-cycle: initial human capital, school taste, and adult income shocks. See main text for details.*

are smaller than those given by the initial human capital process.

**Adult income shocks** Finally, we study the role of adult income risk by simulating an economy with no shocks to labor income (fifth column of Table 7). In this environment, inequality is reduced by 31% (the variance of log lifetime earnings decreases from 0.406 to 0.279). The intuition is very simple: Even if agents enter the labor market with similar conditions, income shocks spread them across the income distribution. The absence of labor income shocks, thus, reduces the variance of lifetime earnings.

Labor income shocks also make it possible for agents with disadvantaged initial conditions to earn similar levels of income as agents with better initial conditions. Consequently, we find that an economy without labor income shocks would also have lower intergenerational mobility (the rank-rank correlation increases from 0.283 to 0.295). Even though they are not directly comparable, the magnitude of the effects suggest that labor income shocks may have a larger impact on inequality than on intergenerational mobility.

# 5 Conclusion

This paper analyzes the roots of social immobility and income inequality, trying to disentangle the importance of differences in initial conditions determined early in life relative to differences in experiences over the working lifetime. We use a standard heterogeneous agent life-cycle model with idiosyncratic risk and incomplete markets extended to account for the role of families (through endogenous fertility, family transfers, and education) in determining initial opportunities. The model also allows for human capital transmission from parents to children. We propose that fertility differentials between rich and poor households can lead to substantial differences in the resources available for children, which can be important for their adult outcomes. The model is able to capture evidence on the relation between fertility differentials, income inequality, and intergenerational mobility. Income risk is calibrated to include total earnings variation, encompassing what may be considered both wage shocks and hours-worked differences. Typical statistics on adult income risk are well captured by the model, which is required for an impartial comparison of the importance of adult risk relative to initial conditions.

We find that initial conditions (as of age 14) account for 60% of the lifetime earnings inequality, while adult income risk over the working life accounts for the remaining 40%. Relative to our baseline estimation for the US in the 2000s, we find that an economy without fertility differentials would have 7% higher intergenerational mobility and 1% lower income inequality. The impact of a counterfactual constant transfer per child are twice as large. Even though fertility differentials play a smaller role relative to parental transfers in the US, this may not be the case for other countries with larger fertility differentials. According to our model, this implies that policies that reduce the incentives of poorer households to have children may be successful in improving inequality and social mobility in such countries.

Consistent with the early-childhood investment literature (Heckman et al., 2010; Gertler et al., 2014), we find that the stochastic process for the initial human capital (i.e., the correlation between parents' human capital and the variance of the process) is an important factor to understand income inequality and social mobility. Policies that are successful in increasing the resources available to all children earlier in life may reduce inequality and improve intergenerational mobility (e.g., Daruich, 2018). The objective of this paper, however, is to study the role of fertility and family transfers so we model this stochastic process as an exogenous shock disciplined by the data. Our results suggest that policies that affect initial human capital may have sizable effects on fertility and transfer choices. Thus, studies of human capital policies that abstract from fertility and family transfers choices may be biased in their results.

Doepke and Tertilt (2016) argue that there is a potentially large role for family economics within macroeconomics. Our results are consistent with this: those interested in understanding inequality, intergenerational mobility, or inequality of opportunity may need to take fertility differentials and family transfers into account.

# References


Abbott, B., G. Gallipoli, C. Meghir, and G. L. Violante (Forthcoming). Education Policy and Intergenerational Transfers in Equilibrium. Technical report.

Altonji, J. G., F. Hayashi, and L. J. Kotlikoff (1997). Parental altruism and inter vivos transfers: Theory and evidence. *Journal of Political Economy 105*(6), 1121–1166.

Autor, D. H., L. F. Katz, and M. S. Kearney (2008, May). Trends in U.S. Wage Inequality: Revising the Revisionists. *The Review of Economics and Statistics 90*(2), 300–323.

Barro, R. J. and G. S. Becker (1989, March). Fertility Choice in a Model of Economic Growth. *Econometrica 57*(2), 481–501.

Benhabib, J., A. Bisin, and M. Luo (2015, November). Wealth distribution and social mobility in the us: A quantitative approach. Working Paper 21721, National Bureau of Economic Research.

Checchi, D., A. Ichino, and A. Rustichini (1999, December). More equal but less mobile?: Education financing and intergenerational mobility in Italy and in the US. *Journal of Public Economics 74*(3), 351–393.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014). Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Quarterly Journal of Economics 129*(4), 1553–1623.

Corak, M. (2013, Summer). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. *Journal of Economic Perspectives 27*(3), 79–102.

Cunha, F., J. J. Heckman, and S. M. Schennach (2010, 05). Estimating the Technology of Cognitive and Noncognitive Skill Formation. *Econometrica 78*(3), 883–931.

Daruich, D. (2018). The macroeconomic consequences of early childhood development policies. Working paper.

de la Croix, D. and M. Doepke (2003, September). Inequality and Growth: Why Differential Fertility Matters. *American Economic Review 93*(4), 1091–1113.

de la Croix, D. and M. Doepke (2004). Public versus private education when differential fertility matters. *Journal of Development Economics 73*(2), 607–629.

de la Croix, D. and M. Doepke (2009). To segregate or to integrate: Education politics and democracy. *Review of Economic Studies 76*(2), 597–628.

Doepke, M. and M. Tertilt (2016). *Families in Macroeconomics*, Volume 2 of *Handbook of Macroeconomics*. Elsevier.

Fella, G. (2014, April). A Generalized Endogenous Grid Method for Non-smooth and Non-concave Problems. *Review of Economic Dynamics 17*(2), 329–344.

Fernandez, R., N. Guner, and J. Knowles (2005, January). Love and Money: A Theoretical and Empirical Analysis of Household Sorting and Inequality. *The Quarterly Journal of Economics 120*(1), 273–344.

Fernandez, R. and R. Rogerson (2001, November). Sorting And Long-Run Inequality. *The Quarterly Journal of Economics 116*(4), 1305–1341.

Flood, S., M. King, S. Ruggles, and J. R. Warren. (2015). Integrated Public Use Microdata Series, Current Population Survey: Version 4.0. [Machine-readable database]. Minneapolis: University of Minnesota.

Folbre, N. (2009). *Valuing children: rethinking the economics of the family*. The Family and Public Policy. Harvard University Press.

Gertler, P., J. J. Heckman, R. Pinto, A. Zanolini, C. Vermeersch, S. Walker, S. M. Chang, and S. Grantham-McGregor (2014). Labor market returns to an early childhood stimulation intervention in jamaica. *Science 344*(6187), 998–1001.

Gross, D. B. and N. S. Souleles (2002). Do liquidity constraints and interest rates matter for consumer behavior? evidence from credit card data*. *The Quarterly Journal of Economics 117*(1), 149–185.

Heathcote, J., K. Storesletten, and G. L. Violante (2010). The macroeconomic implications of rising wage inequality in the united states. *Journal of Political Economy 118*(4), 681–722.

Heckman, J. J., L. J. Lochner, and P. E. Todd (2006, June). *Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond.* , Volume 1 of *Handbook of the Economics of Education*, Chapter 7, pp. 307–458. Elsevier.

Heckman, J. J., S. H. Moon, R. Pinto, P. Savelyev, and A. Yavitz (2010). Analyzing social experiments as implemented: A reexamination of the evidence from the highscope perry preschool program. *Quantitative Economics 1*(1), 1–46.

Huggett, M., G. Ventura, and A. Yaron (2011, December). Sources of Lifetime Inequality. *American Economic Review 101*(7), 2923–54.

Jones, L. E. and A. Schoonbroodt (2010). Complements versus substitutes and trends in fertility choice in dynastic models. *International Economic Review 51*(3), 671–699.

Jones, L. E. and M. Tertilt (2008). *An Economic History of Fertility in the U.S.: 1826-1960.* , Chapter 5, pp. 165–230. Frontiers of Family Economics. Emerald.

Keane, M. P. and K. I. Wolpin (1997). The career decisions of young men. *Journal of Political Economy 105*(3), pp. 473–522.

Kremer, M. and D. L. Chen (2002, September). Income Distribution Dynamics with Endogenous Fertility. *Journal of Economic Growth 7*(3), 227–58.

Krueger, D. and A. Ludwig (2016). On the optimal provision of social insurance: Progressive taxation versus education subsidies in general equilibrium. *Journal of Monetary Economics 77*, 72 – 98.

Lee, S. Y. and A. Seshadri (2018). Economic policy and equality of opportunity. *The Economic Journal 128*(612), F114–F151.

Lee, S. Y. and A. Seshadri (Forthcoming). On the Intergenerational Transmission of Economic Status. *Journal of Political Economy*.

Luxembourg Income Study (LIS) Database (2014). http://www.lisdatacenter.org (multiple countries; 1981 to 2010). Luxembourg: LIS.

Manuelli, R. E. and A. Seshadri (2009, May). Explaining International Fertility Differences. *The Quarterly Journal of Economics 124*(2), 771–807.

Minnesota Population Center. (2014). Integrated Public Use Microdata Series, International: Version 6.3 [Machine-readable database]. Minneapolis: University of Minnesota.

Moav, O. (2005). Cheap children and the persistence of poverty. *The Economic Journal 115*(500), 88–110.

Murnane, R. J., J. B. Willett, and F. Levy (1995). The growing importance of cognitive skills in wage determination. *The Review of Economics and Statistics 77*(2), 251–266.

Nardi, M. D. and F. Yang (2016). Wealth inequality, family background, and estate taxation. *Journal of Monetary Economics 77*, 130 – 145.

Restuccia, D. and C. Urrutia (2004). Intergenerational persistence of earnings: The role of early and college education. *The American Economic Review 94*(5), pp. 1354–1378.

Roys, N. and A. Seshadri (2014). On the Origin and Causes of Economic Growth. Working paper.

Ruggles, S., K. Genadek, R. Goeken, J. Grover, and M. Sobek. (2015). Integrated Public Use Microdata Series: Version 6.0 [Machine-readable database]. Minneapolis: University of Minnesota.

Smets, F. and R. Wouters (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American Economic Review 97*(3), 586–606.

Yum, M. (2018). Parental time investment and intergenerational mobility. Working paper.

# Appendix

## A Empirical Findings: Details

### A.1 Fertility and Income

Economic models focus on the decisions made by individual households. Consequently, we would like a measure of fertility decisions at the household level. Probably the closest measure to this is Children Ever Born (CEB), available from the US Census. This variable asks each woman how many children they had had during their lives and allows researchers to compute fertility rates by cohorts. Unfortunately, this variable has some limitations. First, it requires women's fertility period to be over to be of use for our purposes. Even assuming that child-bearing age extends only to forty years old, using the most current census possible only women born 40 years ago could be used. Notice also that choosing the upper end of the age that determines the sample can bring issues. For example, if we used women up to any age we might get biased measures of fertility if this is correlated with mortality risk. Last but not least, this variable has even been dropped from the US Census after 1990. Hence, we use an alternative measure of fertility for our main analysis but use CEB to evaluate the robustness of our results.

For the sake of clarity let us introduce the most basic measure of fertility, the Crude Birth Rate (CBR), which is defined as the ratio of births to women alive in one year. A typical issue with the CBR is that it can be too low because of a big share of women who have already passed child-bearing age but are still bringing the ratio down. The Total Fertility Rate (TFR) attempts to correct some of these issues. It is defined as the sum of the age-specific birth rates over all women alive in a given year. Hence, under the same example, if there is an unusually large number of women outside of the child-bearing age, TFR is not affected. Formally, let $f_{a,s,t}$ be the number of children born to women of age $a$ in region $s$ and period $t$ divided by the number of women of age $a$ in region $s$ and period $t$. Assume that the child-bearing age extends between ages $a_L$ and $a_H$.[25] Then the TFR in region $s$ and period $t$, $\text{TFR}_{s,t}$, is defined as

$$\text{TFR}_{s,t} = \sum_{a=a_L}^{a=a_H} f_{a,s,t}. \tag{11}$$

Typically these age-specific fertility rates are constructed for ages bands in increments of 5 years and then summed, with the limits of the sum being $a_L = 15$ and $a_H = 49$.[26] Relative to CEB, the main benefit is that it does not require the data to report how many children each woman has had. Instead, it only needs children under the age of one to be associated with their mothers within the household—a much more standard requirement. Moreover, TFR does not require women to have passed the child-bearing age as it focuses on fertility rates, which are not associated with a particular cohort but with women currently alive. Hence, information on the TFR is more up to date than that of the CEB. For this and other reasons, TFR has been used widely in the literature (Kremer and Chen, 2002; Manuelli and Seshadri, 2009).[27]

To connect the fertility rate with income, we define the TFR conditional on the income group. Suppose we groups the mothers into quantiles according to their household income. Then, let $f_{a,q,s,t}$ be the number of children born to women of age $a$ within quantile $q$ in region $s$ and period $t$ divided by the number of women of age $a$ and income quantile $q$ in region $s$ and in period $t$. Then, the TFR of income quantile $q$ in region $s$ and period $t$, $\text{TFR}_{q,s,t}$, is defined as

$$\text{TFR}_{q,s,t} = \sum_{a=15}^{a=49} f_{a,q,s,t}. \tag{12}$$

The appropriate measure of income is not obvious either. Assuming households have perfect foresight of their income, using their lifetime income would probably be the best measure. Jones

[25]Notice that, assuming most women have children only in that period, extending this sample would most likely add only values of zeros to the formula of the TFR.

[26]Notice that when using age bands of increments longer than one year (but having only one year of data), $f_{a,s,t}$ is calculated as the number of children born to women within age band $A$ in region $s$ and in year $t$ divided by the number of women within age band $A$ in region $s$ and in year $t$, *multiplied by the length of age band $A$*.

[27]The TFR measure of fertility also has its weaknesses. Since it is computed using data from a given year, it mixes fertility decisions of the different birth cohorts alive at the time. If all of these had the same fertility decisions, both CEB and TFR would be identical. However, if fertility rates are changing from cohort to cohort, then CEB gives the more accurate picture of fertility decision. Given the data limitations, however, we do our empirical work based on the TFR measure of fertility.

and Tertilt (2008) use "Occupation Income" as their measure of choice. This is constructed for year 1950 by IPUMS, and the authors extend it to their whole period of interest by assuming a constant 2% annual increase, equal across all occupations. This assumption does not seem harmless, because occupations change their relative importance over time (e.g., Autor et al., 2008). Moreover, there is a substantial variation in income across people within a given occupation.[28] Hence, we focus on annual total household income in the year of the sample. To get the appropriate quantile groups, we cannot compare the income level of young and old households, because, following the typical life cycle of income, young households tend to have lower incomes. Hence, we define quantiles within the appropriate age group used for the TFR calculation.[29] This way the TFR for each quantile-region-year can be estimated.

We consider alternative measures in our robustness analysis reported in Figure 3. To compute the TFR gap between education groups, we calculate the TFR as in Equation (11) but separately for each education group. Then, we calculate the difference in the TFR between women married to college-graduate men and those married to high school dropout men. We use men's education to avoid introducing issues regarding changes in women's educational attainment patterns over time. For the robustness analysis using CEB elasticity, we focus on women between ages 40 and 49 and use the same income measure and methodology used for the TFR elasticity.

## A.2 Fertility Estimation: Sample Selection

For each year of the US Census, we start with all women belonging to the main family of each household and with non-missing family income. We drop women outside of the "age of fertility"; i.e., 15 to 49 years old. Then, we restrict our attention to those who are either heads

[28]For example, see the *National Compensation Survey: Occupational Wages in the United States, July 2004, Supplementary Tables* (Bureau of Labor Statistics, August 2005), p. 3; on the Internet at http://www.bls.gov/ncs/ocs/sp/ncbl0728.pdf (visited Jan. 21, 2015).

[29]For example, for households within the age group 15-19 years old, income quantiles are defined among other households in the same age group. Moreover, we use a second-degree polynomial on age within each age group to approximate each family's income at a fixed constant age within each age group and further reduce this concern. However, results do not change significantly if we omit this last step.

of households or spouses of heads of households and report as married. Finally, we drop those who report as in school or whose annual household income (in 2000 US$) is less than $4,000. Each entry of Table A.1 shows the number of women after each selection procedure, in the corresponding year.

Table A.1: **Sample Selection.**

| | 1960 | 1970 | 1980 | 1990 | 2000 | 2010 |
|---|---|---|---|---|---|---|
| Women in main family without missing income | 4,132,162 | 3,821,829 | 5,313,266 | 5,789,849 | 6,357,343 | 6,860,823 |
| Age≥15 & age≤49 | 1,946,343 | 1,806,332 | 2,675,706 | 2,903,974 | 3,087,222 | 2,996,625 |
| Head or spouse | 1,550,987 | 1,369,469 | 2,035,969 | 2,264,903 | 2,411,233 | 2,259,209 |
| Married | 1,395,011 | 1,174,508 | 1,577,704 | 1,694,897 | 1,700,881 | 1,554,153 |
| Not in school | 1,376,347 | 1,158,518 | 1,492,430 | 1,555,541 | 1,581,212 | 1,432,147 |
| Household income≥$4000 | 1,337,549 | 1,142,124 | 1,465,870 | 1,535,536 | 1,561,333 | 1,422,478 |

*Source: Census. Each row reports the number of women in each year after dropping all observations without the characteristics given by that row and those above it. HH Income refers to the annual income at the household level in real terms (2000 US$).*

After doing this sample restriction, we estimate the fertility rates and elasticities only in states with samples of more than 1,500 women, to avoid using small, noisy estimates in our main analysis of the relation between fertility differentials and average income levels. Moreover, when computing the TFR, we require each of the seven age groups (15–19, 20–24,...,45-49) to have at least 50 women and 1.5% of the women in the state's sample. We do this in order to avoid using small age-groups, which can add noise to the estimation of the TFR—particularly important for younger age groups since we are focusing on married women. We have tried alternative selection procedures and found results to be qualitatively similar.

## A.3 Additional Figures and Tables

Table A.2 reports the results from regressing fertility rate (TFR) on the log of average household income, calculated for each state-year using the main sample selection criteria explained in Appendix A.2.

Table A.2: **How the TFR changes with Average Household Income**.

| | (1) | (2) | (3) |
|---|---|---|---|
| Ln(Avg. Household Income) | -0.398*** | -0.465*** | -0.0539 |
| | (0.0319) | (0.0315) | (0.213) |
| | | | |
| Observations | 298 | 298 | 298 |
| R-squared | 0.281 | 0.547 | 0.763 |
| # of States | 51 | 51 | 51 |
| State FE | NO | YES | YES |
| Year FE | NO | NO | YES |

*Robust standard errors in parentheses. *, **, *** denote statistical significance at the 10, 5, and 1 percent level, respectively. Source: Census. Years: 1960, 1970, 1980, 1990, 2000, and 2010. Methodology is explained in the main text.*

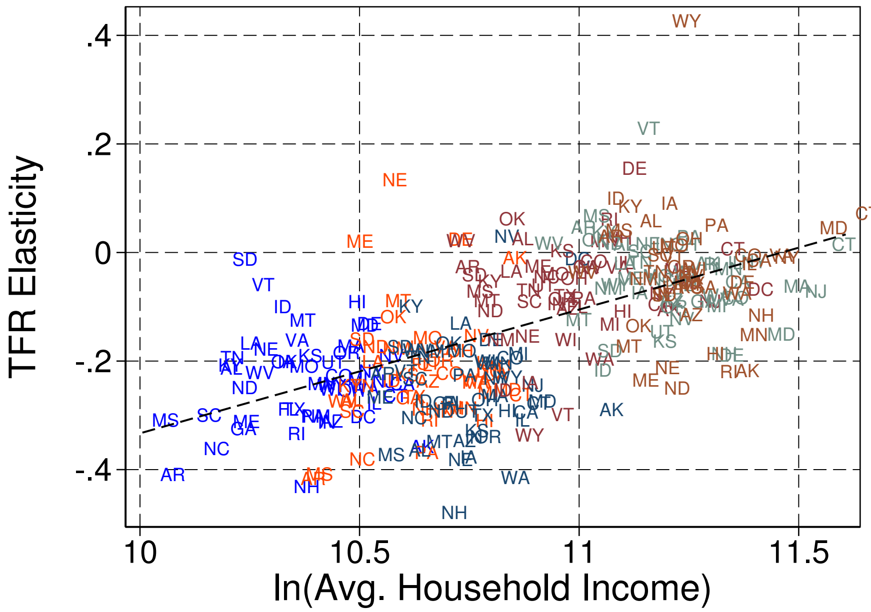
Figures A.1 and A.2 report all the observations used in Figures 2 and 3, respectively.

# B Estimation and Results: Details

## B.1 Income Profile: Sample Selection

We start with 2,900,310 married households from the 2000 US Census data available from IPUMS. We drop the households whose heads are reported to be in school: This reduces the sample to 2,728,958. Dropping households who report yearly household income below $8,000 (equivalent to 50 weeks of 20 hours of work at an hourly wage of $8) further reduces the sample to 2,174,358. Finally, we drop households whose head is outside the age range of 24-63, which gives us a final sample of 1,501,006. When we split this sample into 3 education groups, we get a high-school dropouts sample of 144,935 households, a high-school graduates sample of 891,306 households, and a college graduates sample of 464,765 households.

Figure A.1: **Elasticity of fertility to income and GDP: All observations**.

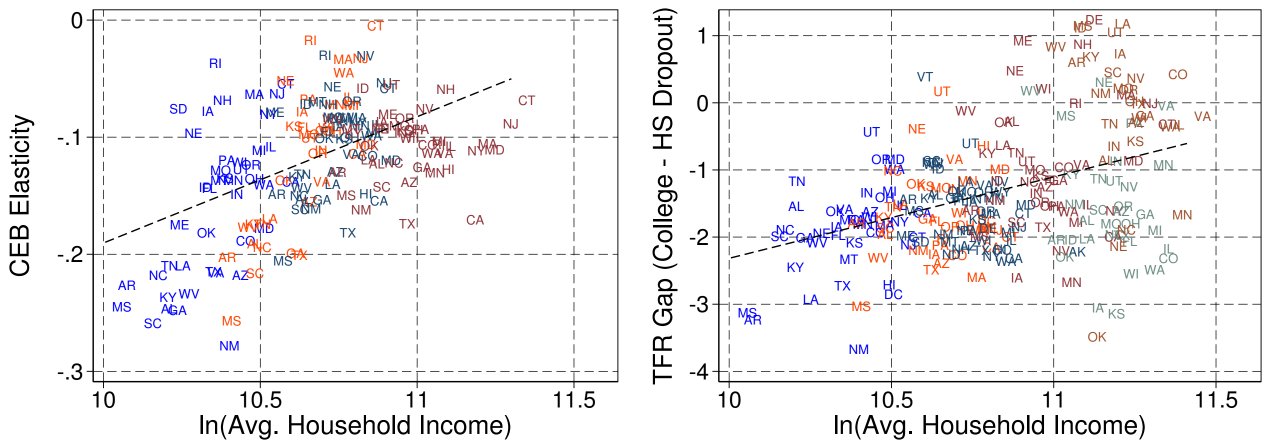



*Source: Census. Years: 1960, 1970, 1980, 1990, 2000, and 2010. For each state-year we estimate the elasticity of fertility to income* (1)*. Each census year is represented by a different color. Methodology is explained in the main text.*

## B.2 Replacement Benefits: US Social Security System

The pension replacement rate is obtained from the Old Age Insurance of the US Social Security System. We use education level as well as the level of human capital at the moment of retirement to estimate the average lifetime income, on which the replacement benefit is based. With the last level of human capital before retirement $h$ and the education level $e$, we estimate the average lifetime income to be $\widehat{y}(h) = \bar{h}(\mathrm{e}) \times h$ with $\bar{h}$ equal to 0.98, 1.17, and 0.98 for high-school dropouts, high-school graduates, and college graduates, respectively. Then, average annual income $\widehat{y}$ is used in Equation (13) to obtain the replacement benefits.

Figure A.2: **Robustness of fertility differentials: All observations.**




*Source: Census. Years: 1960, 1970, 1980, 1990, 2000, and 2010. Each census year is represented by a different color. Methodology is explained in the main text.*

The pension formula is given by

$$\pi(h) = \begin{cases} 0.9\widehat{y}(h) & \text{if } \widehat{y}(h) \leq 0.3\bar{y} \\ 0.9(0.3\bar{y}) + 0.32(\widehat{y}(h) - 0.3\bar{y}) & \text{if } 0.3\bar{y} \leq \widehat{y}(h) \leq 2\bar{y} \\ 0.9(0.3\bar{y}) + 0.32(2 - 0.3)\bar{y} + 0.15(\widehat{y}(h) - 2\bar{y}) & \text{if } 2\bar{y} \leq \widehat{y}(h) \leq 4.1\bar{y} \\ 0.9(0.3\bar{y}) + 0.32(2 - 0.3)\bar{y} + 0.15(4.1 - 2)\bar{y} & \text{if } 4.1\bar{y} \leq \widehat{y}(h), \end{cases} \tag{13}$$

where $\bar{y}$ is approximately \$70,000.

## B.3 Validation of Persistence of Income Process

We estimate an income process similar to Heathcote et al. (2010), but using household income and 2-year periods instead. We propose that log earnings of household $i$, with age $j$ and education $e$ in period $t$ are represented by

$$\ln(\text{Earnings}_{i,j,e,t}) = \ln(w_{e,t}) + \mu_{j,e} + u_{i,j,e,t},$$

where $w_{e,t}$ is the wage for all labor supplied by those with education $e$ at time $t$, $\mu_{j,e}$ is the age profile, and $u_{i,j,e,t}$ is the idiosyncratic shock.

From these regressions we obtain the stochastic residual component $u_{i,j,e,t}$. We then model the unobservable shock $u_{i,j,e,t}$ as the sum of two independent components

$$u_{i,j,e,t} = z_{i,j,e,t} + m_{i,j,e,t},$$

where $z_{i,j,e,t}$ is a persistent shock assumed to have an AR(1) structure

$$\begin{aligned} z_{i,j,e,t} &= \rho^e z_{i,j-1,e,t-1} + v_{i,j,e,t} \\ v_{i,j,e,t} &\sim N(0, \sigma_v^e), \end{aligned}$$

and $m_{i,j,e,t} \sim N(0, \sigma_m^e)$ is measurement error (and noise from the point of view of the model). The initial draw is $z_{i,0,e,t} \sim N(0, \sigma_{z_0}^e)$. Note that $\rho^e$, $\sigma_{z_0}^e$, $\sigma_v^e$, and $\sigma_m^e$ may depend on the education group but are assumed to be independent over time. So we have 12 parameters to estimate, which we will do independently for each education group using a Minimum Distance Estimator.