Sources of lifetime inequality revisited

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Abstract

Factors established early in life can be key determinants of the lifetime value of earnings, consumption and wealth. Furthermore, some of these variables are determined by parental background (ability, human capital) or passed on directly from parents (wealth). In this paper, I study a life cycle - overlapping generations economy with borrowing constraints and costly human capital acquisition, in which initial conditions are determined by parental background. The cost of human capital may prevent constrained agents to optimally acquire human capital and intergenerational transmission of wealth may alleviate this effect for wealthy households. Using data from the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY), I document statistics of the evolution of cohort inequality and the importance of parental transfer to attend college. I find that initial conditions can explain about 10% of the variation in lifetime income and wealth. Relaxing borrowing increases college enrollment and decreases inequality. The intergenerational correlation of abilities explains more than half of the intergenerational income elasticity, suggesting an important role for the parental background.

1 Introduction

How important are initial conditions to determine one's lifetime welfare, in terms of consumption, income and wealth? Initial conditions, such as one's cognitive ability or wealth can have a sizable impact on future income. High ability individuals are capable to increase their human capital faster and thus obtain higher future earnings. Financial

wealth allows smoothing out adverse economic shocks, increasing consumption level, and even to get specific skills by attending college. Furthermore, these initial conditions strongly depend on the parental background. Abilities can be transmitted through genes. Financial wealth can be directly transmitted to descendants.

Some authors such as Piketty (2014) and others have argued that financial wealth has become more important to determine one's life outcomes. Others, such as Huggett, Ventura, and Yaron (2011) argue that financial wealth has little impact to determine one's lifetime welfare and the observed inequality. To assess the importance of initial condition it is important to take into account both parental background and financial markets.

In this paper, I assess the impact of initial conditions on lifetime welfare. In particular, I study the role of parental background and wealth, and how these intergenerational links contribute to shaping the observed inequality.

I develop a quantitative model with a life cycle - overlapping generation structure and altruistic parents. Agents are heterogeneous in three dimensions: wealth, innate ability, and human capital. Innate ability is fixed in a lifetime and correlated across generations. Individuals with high ability accumulate human capital faster. Agents go through three different stages: education, work, and retirement. Education allows them to acquire skills specific to more productive sectors, and as a result, they get a higher wage per unit of human capital provided in the market. To get a higher education, they need financial resources obtained from parents. During the work-stage, agents save for retirement and to transfer to their kids. In retirement periods, agents live off a pension provided by the government and their savings.

Using data from the Panel Study of Income Dynamics, I show the evolution of mean earnings and the evolution of inequality (Gini coefficient) of a cohort during the life cycle. I also provide evidence of the probability of attending college conditional on parental education. Finally, I show evidence of the importance of wealth to attend college. In particular, data suggest that in recent years wealth is much more important than it used to be in previous decades.

Using data from the National Longitudinal Study of Youth 79 (NLSY79) and National Longitudinal Study of Youth 79 Children and Young adults (NLSY79 Child/YA), I show that the intergenerational correlation of abilities is between 0.3 and 0.4. Using data from the National Longitudinal Study of Youth 97, I show the importance of parental transfers in obtaining higher education. I show that the distribution of transfers is highly skewed.

I estimate a logit model and show that the parental transfers are statistically significant, under several specifications.

The model replicates the most salient features of the data regarding income profiles (average, low- and high-educated agents), the share of college students, the evolution of Gini coefficient conditional on age, and share of agents with no parental transfers. The calibrated model suggests that parental wealth has a great impact on determining lifetime welfare. An agent in the 75th percentile of the initial wealth distribution has 8% higher lifetime earnings than an agent with median wealth. Agents in the 75th percentile of the ability distribution have 20% higher earnings than the agent with the median ability. Variance decomposition analysis suggests that roughly 10% of the observed cohort inequality in income and wealth is due to initial conditions.

Improving credit access decreases life-cycle inequality. More agents are allowed to enroll in college, average earnings increases and Gini coefficients decrease. The parental background is key to understand the social mobility observed in the data. Shutting down the intergenerational correlation of abilities decreases the intergenerational income elasticity by half. Intergenerational income mobility is explained by correlations of abilities across generations and shocks received during the life cycle. Wealth has a limited role in explaining income mobility. The rise in college tuition and skilled biased technical change do not seem to have a great impact on how much initial conditions explain variations in lifetime welfare.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes the life cycle model. Section 4 uses PSID and NLSY data to show the evolution over the life cycle of mean earnings and several measures of inequality for a particular cohort, as well as the importance of parental education, financial wealth and transfer in the process of human capital investment. Section 5 discusses the calibration and Section 6 discusses the model fit and performs quantitative exercises. Section 7 concludes.

2 Related Literature

The idea of intergenerational transmission of wealth from parents to children and human capital accumulation dates back to Loury (1981). In his model, parents are subject to borrowing constraints and therefore they may not be able to optimally invest in their child's human capital. This mechanism endogenously generates the earnings distribution in the

economy. Despite that this mechanism has been well-known for a long time, the quantitative impact of this mechanism has not been explored in quantitative macroeconomic models.

There are several papers studying intergenerational transmission of wealth, De Nardi (2004), Boar (2018), Luo (2017), to name a few. Most of them study bequests and/or intervivos transfers, but none of them study the relationship between transfers and human capital accumulation.

There is a vast strand of literature studying earnings dynamics over the life cycle, for instance, Storesletten et al. (2004), Huggett et al. (2006), Guvenen (2009). See Meghir and Pistaferri (2011) for a survey.

Daruich (2019) studies an economy with intervivos transfers and human capital accumulation, where parents influence their child's human capital by investing time and money. His focus is different in that he studies the macroeconomic implication of changing schooling financing by changing the tax policy, whereas my focus is to quantitatively disentangle the effects of initial conditions, namely the learning ability, initial human capital and initial wealth, to explain the lifetime inequality.

Credit constraints and human capital acquisition have been studied in Lochner and Monge-naranjo (2016) and Hai and Heckman (2017). They focus on the interaction of credit constraints human capital rather than their implications for inequality and welfare.

Abbott et al. (2013) study an economy where financial frictions play a role in human capital acquisition. Their main focus is the implication of education policy in determining intervivos transfers.

The relative importance of shocks versus initial conditions to explain lifetime welfare has been studied in Huggett et al. (2006) and Huggett et al. (2011). My paper contributes to this literature by reassessing the relative contribution of each factor in an economy with intergenerational links across generations and costly human capital accumulation.

3 Economic Environment

Demographics: Life cycle model with overlapping generation structure and deterministic finite lives. At age 30 agents have a child. Agents die for sure at age 80.

Heterogeneity: Agents are heterogeneous in innate ability θ, human capital h and fi-

nancial assets a. Innate ability is determined at the time of birth and is fixed throughout the agent's lifetime. The initial level of human capital (at age 18) is determined by innate ability. I assume that there is an initial level of human capital h_0 that agents are born with. During the first 18 years of life, agents devote all their endowment of time to accumulate human capital. Differences in innate ability generate differences in initial human capital. This mechanism generates a positive correlation between initial human capital and innate ability. [1]. The ability allows agents to acquire human capital faster, so it can be interpreted as learning ability. Agents have two sources of human capital accumulation (i) acquire formal education (going to college) (ii) acquire human capital spending time during their working life (e.g. on the job training), à la Ben-Porath. During the working stage agents receive i.i.d. idiosyncratic shocks to human capital, z_t. Financial assets are accumulated through savings during the lifetime.

Life cycle: Agents go through three stages in their lives: (i) education, (ii) labor and (iii) retirement. In the first stage of their lives, agents decide whether to go to college. This decision depends on their innate ability, initial human capital as well as the availability of financial resources. If they choose to go to college, agents acquire high skill human capital. Otherwise, they stay as low skilled workers. Being high skilled worker can be interpreted as working in certain "occupations", "industries" or "sectors" that pay higher wage rates per unit of human capital.

During their labor stage, agents decide how much time spend on labor activities and how much time to spend acquiring human capital. Human capital is affected by individual investments as well as stochastic shocks. By age 30, the individual's child is born. By age 48 the child becomes an adult and his parent must decide how much wealth to transfer him[2].

During retirement, agents receive social security benefits and no labor earnings. There are no bequests, so agents consume all their wealth at the end of their lives.

[1] Huggett et al. (2011) show that to replicate the increasing inequality over the life cycle a positive correlation between ability and initial human capital is necessary. Guvenen et al. (2013) offer a rationale for this condition. Since agents enter the model at some point in their lifetime, they have already accumulated some human capital in early stages in life. Thus, agents with higher ability accumulate more human capital which generates a positive correlation. This is the exact mechanism used in the periods before the model starts.

[2] It is assumed that once the wealth transfer is made, the child is free to spend those resources in education or consumption. Parents do not have the technology to monitor how kids spend resources nor can make contingent transfers.

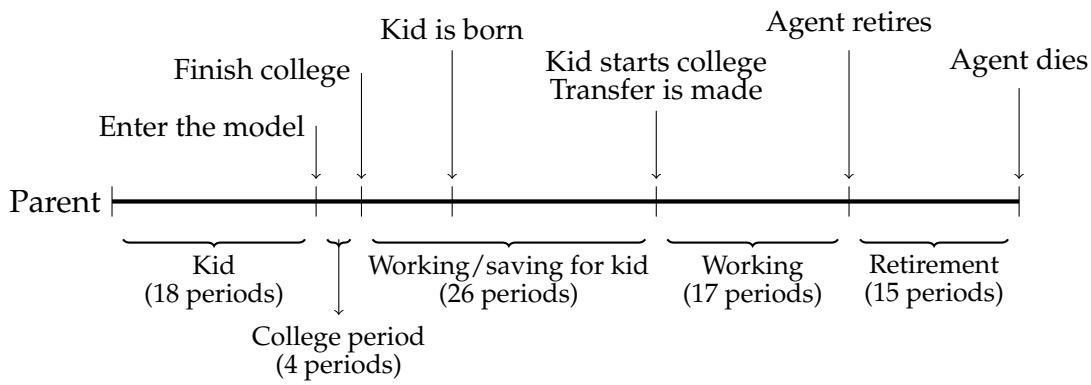


Figure 1: Timeline

Figure 1 shows the timeline of the model.

Intergenerational Links: Innate ability is correlated across generations and follows a process as

$$\log(\theta_{n+1}) = (1 - \rho_\theta)\log(\bar{\theta}) + \rho\log(\theta_n) + \varepsilon \tag{1}$$

where θ_n is the ability of generation n, $\bar{\theta}$ is the log run average of ability, ρ_θ is the intergenerational correlation of ability and ε is an i.i.d. shock with mean zero and variance σ_ε. The intergenerational correlation of abilities generates an intergenerational correlation of initial human capital. This process generates a steady state distribution with mean and variance (in levels) m_θ and v_θ. Wealth is transmitted across generations only through the intervivos transfer, no bequests.

Borrowing constraints: To fully assess the contribution of borrowing constraint to human capital accumulation I use different borrowing limits: (i) no borrowing is allowed, (ii) ad-hoc borrowing limits.

Preferences: Agents have altruistic preferences towards their children. Let U_n be the lifetime utility derived from consumption flow for agent of generation n, $U_n = \sum_{t=1}^{T} \beta^t u(c_t)$, where $u(c_t)$ is increasing and concave function. Individuals maximize the lifetime utility from their own consumption and weight their child's lifetime utility of consumption. They maximize $\mathcal{U}_n = U_n + \tilde{\gamma} U_{n+1}$, where $\tilde{\gamma}$ is the weight parents put on their kid's utility.

Tax schedule and Government spending: The tax and transfer system has two components: an income tax component and a social security system component $T = T^{ss} + T^{inc}$. The social security part consists of a proportional tax τ^{ss} for active workers, and a positive transfer equal to a fraction of average earnings in the economy, as in Huggett et al. (2011).

The income tax schedule captures the effective average income tax rates of the economy as a function of income. In particular, tax rate function $t(\tilde{y}) = 1 - \mu\tilde{y}^{-\tau}$, as in Bernabou (2002) and Heathcote et al. (2014), where $\tilde{y}$ is taxable income. I consider taxable income as the after social security tax labor income plus capital income. Guner et al. (2014) show that this tax function specification provides a reasonable fit to the actual U.S. income tax schedule for both the average tax rates and effective marginal tax rates. The government has a balanced budget every period.

3.1 The Life cycle model

Stage 1: Education stage

Agents choose whether to go to college or not. The value of an agent at time zero, with initial financial wealth a, human capital h and ability θ is:

$$V_0(a, h; \theta) = \max\{V^c(a, h; \theta), V^{nc}(a, h; \theta)\}$$

where $V^c(k, h; a)$ is the value of a college student and V^{nc} is the value of not going to college.

The college student solves

$$\begin{aligned} V_j(a_j, h_j; \theta) &= \max_{c_j, s_j} u(c_j) + \beta \mathbb{E}_z[V_{j+1}(a_{j+1}, h_{j+1}; \theta)] \\ \text{s.t.} \qquad c_j + a_{j+1} &= a_j(1 + r) - P_c \\ h_{j+1} &= ((1 - \delta)h_j + \theta(h_j)^\alpha) \\ a_{j+1} &\geq \underline{a}_{j+1} \end{aligned}$$

If the agent decides to attend college, she spends all her time endowment accumulating human capital. Furthermore, there are no human capital shocks during college. A college graduate works at a wage of w_H per unit of human capital after the education stage.

If the agent chooses not to go to college, she starts working as a low skilled worker and solves

$$
\begin{aligned}
V_j(a_j, h_j; \theta) &= \max_{c_j, s_j} u(c_j) + \beta \mathbb{E}_z[V_{j+1}(a_{j+1}, h_{j+1}; \theta)] \\
\text{s.t.} \qquad c_j + a_{j+1} &= a_j(1+r)a_j + \mu(ra_j + (1-\tau_{ss})w_L h_j(1-s_j))^{1-\tau} \\
h_{j+1} &= \exp(z_{j+1})((1-\delta)h_j + \theta(h_j)^\alpha) \\
a_{j+1} &\geq \underline{a}_{j+1}
\end{aligned}
$$

Stage 2: Working stage

Before Transfer

Agents work either as a high skilled worker or low skilled worker, depending on whether they go to college. High skilled workers receive a wage of w_H per unit of time and human capital, whereas low skilled workers receive w_L.

During this stage, agents have incentives to save for three motives: (i) self-insurance and smooth consumption, (ii) transfer wealth to kids, (iii) save for retirement.

The value function of a worker hired at a wage rate w, with assets a, human capital h and ability θ is

$$
\begin{aligned}
V_j(a_j, h_j; \theta) &= \max_{c_j, s_j} u(c_j) + \beta \mathbb{E}_z[V_{j+1}(a_{j+1}, h_{j+1}; \theta)] \\
\text{s.t.} \qquad c_j + a_{j+1} &= a_j + \mu(ra_j + (1-\tau_{ss})wh_j(1-s_j))^{1-\tau} \\
h_{j+1} &= \exp(z_{j+1})((1-\delta)h_j + \theta(s_j h_j)^\alpha) \\
a_{j+1} &\geq \underline{a}_{j+1}
\end{aligned}
$$

Transfer

At age 48, when the individual's child becomes an adult, the parent transfers resources to the kid. At this age, the value function is

$$
\begin{aligned}
V_j(a_j, h_j; \theta) &= \max_{c_j, s_j, tr} u(c_j) + \beta \mathbb{E}_z[V_{j+1}(a_{j+1}, h_{j+1}; \theta)] + \gamma \mathbb{E}_{\theta'}[V(tr; \theta')] \\
\text{s.t.} \qquad c_j + a_{j+1} + tr &= a_j + \mu(ra_j + (1-\tau_{ss})wh_j(1-s_j))^{1-\tau} \\
h_{j+1} &= \exp(z_{j+1})((1-\delta)h_j + \theta(s_j h_j)^\alpha) \\
a_{j+1} &\geq \underline{a}_{j+1}
\end{aligned}
$$

where $\mathbb{E}_{\theta',\epsilon}[V(tr;\theta')]$ is the expected value of lifetime utility of the son with initial wealth tr. The expectation operator is over the child's ability θ'.

After transfer

Once the transfer has been made, agents accumulate wealth only for retirement and smooth consumption. They solve:

$$
\begin{aligned}
V_j(a_j, h_j; \theta) &= \max_{c_j, s_j} u(c_j) + \beta \mathbb{E}_z[V_{j+1}(a_{j+1}, h_{j+1}; \theta)] \\
\text{s.t.} \qquad c_j + a_{j+1} &= a_j(1+r) + \mu(ra_j + (1-\tau_{ss})w_L h_j(1-s_j))^{1-\tau} \\
h_{j+1} &= \exp(z_{j+1})((1-\delta)h_j + \theta(h_j)^{\alpha}) \\
a_{j+1} &\geq \underline{a}_{j+1}
\end{aligned}
$$

Stage 3: Retirement

Retirees live off their wealth and receive a constant pension benefit p. The retirees' problem is

$$
\begin{aligned}
V(a_j) &= \max_{c_j} + \beta V(a_{j+1}) \\
\text{s.t.} \qquad c_j + a_{j+1} &= p + (1+r)a_j
\end{aligned}
$$

3.2 Equilibrium

A Steady State Equilibrium is a set of policy functions $\{c_t, s_t\}_{j=1}^{J}$, value functions $\{V_t(s;\theta)\}_{j=1}^{J}$ and distribution over states $\{g_t(s,\theta)\}_{j=1}^{J}$ such that given factor prices r, w_L, w_H, government spending and tax schedule $\{T, G\}$ and initial distribution over states $g_0(s,\theta)$:

1. Given prices and government policies, policy functions and value functions solve the individual's problem.

2. Distributions are stationary and consistent with policy functions.

4 Empirical Analysis

In this section, I start describing the data sources and the sample selection criteria. Then I report several facts. First, I document mean income profiles and inequality measures by cohort. Next, I document income profiles by education. Then I document the persistence of education levels across generations. Afterward, I document the levels of educational attainment by wealth class. Finally, I document the probability of attending college conditional on parental transfers.

4.1 Data sources

The Panel Study of Income Dynamics started in 1968 and surveys more than 18.000 individuals from 5.000 families and over five generations, representative of the United States population. Annual waves up to 1997 and biannually since then. It collects data on family and individuals, with more details on household head and wife. After a child leaves home and forms his household, his family is also part of the survey. I use mainly information on the household head.

The National Longitudinal Survey of Youth (NLSY) surveys individuals aged 14 to 22 at the time of their first interview. There are two different cohorts, NLSY79 which is first interviewed in 1979 and NLSY97 which interviews youths for the first time in 1997. After the first interview, they follow the cohort with annual or biannual surveys. NLSY79 and NSL97 have a sample size of around 12,000 and 9,000 individuals, respectively. The NLSY79 Children and Young adults interviews the children of the women in the NLSY79. I use information from these surveys to compute information on earnings, on the transmission of abilities and parental transfers during young ages.

4.2 Income profiles in the PSID

To compute income profiles I focus on male household heads from the SCR sample (nationally representative). For individuals aged less or equal than 30, they have to work more than 260 hours a year and earn at least $1,000 a year (1970 dollars). Individuals older than 30 are kept in the sample if they earn at least $1,500 and work more than 520 hours. To construct statistics, I consider a 5-year bin for each age.

Ideally, I would like to estimate the age profile for several statistics by estimating the

following regression

$$\text{stat}_{i,j} = \text{age effect}_i + \text{time effect}_j + \text{cohort effect}_c + \varepsilon_{i,j} \tag{2}$$

where $stat_i$ is the statistics of interest for age i.

To estimate this equation I can control for either time fixed effect or cohort fixed effect. Controlling for both is not possible since age, time and year are collinear. Heathcote et al. (2005) argue that time effects seem more important than cohort effects. I show age profiles controlling for time effects since I will use these moments to discipline the model.

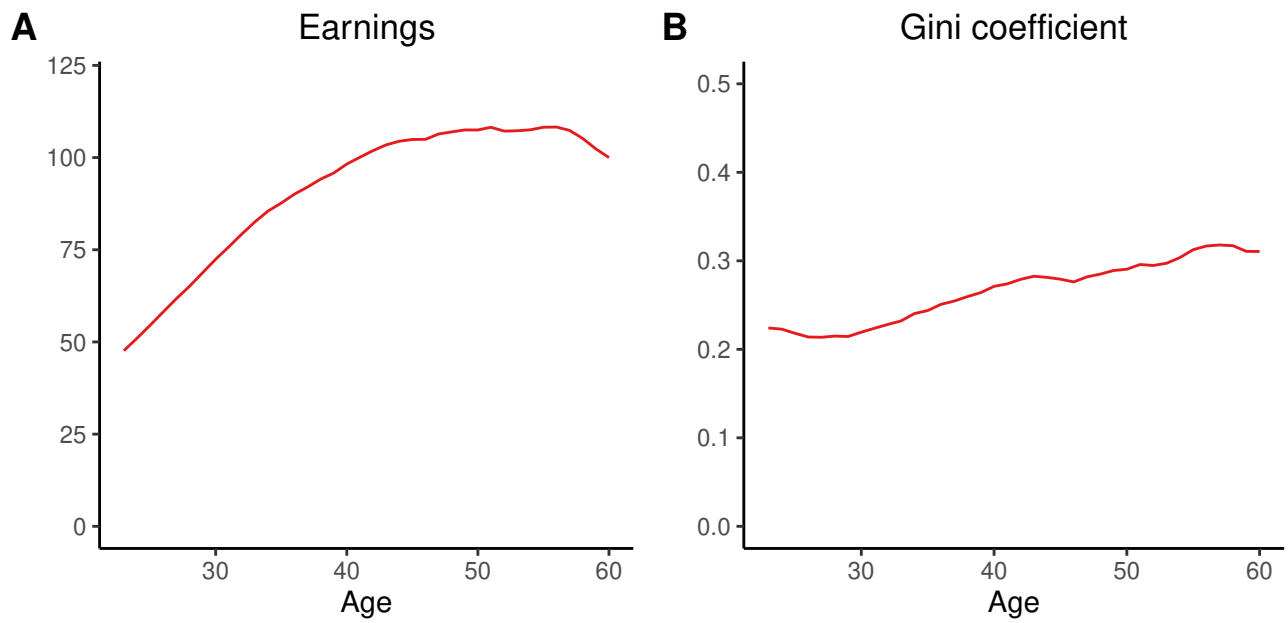


Figure 2: mean earnings and Gini by age

Panel A in Figure 2 shows the mean earnings age profile. The mean earnings profile displays an increasing and concave pattern, it plateaus at around 50 years and it decreases in the late fifties.

Panel B in Figure 2 displays the evolution of cohort earnings inequality as the cohort ages. The pattern is increasing with no clear concavity. The Gini coefficient starts from 0.2 at 23 years old and increases up to 0.3 by the end of the working life.

4.3 Incomes profiles by education

Now I focus on just mean earnings, and compute the same statistical model as (2) with two different subsamples: one with college-educated individuals and one with the level of education less or equal than high school graduate. I use the same criteria as the previous section to select the sample.

Figure 3 shows the income profile for college-educated and non-college educated workers using PSID data.

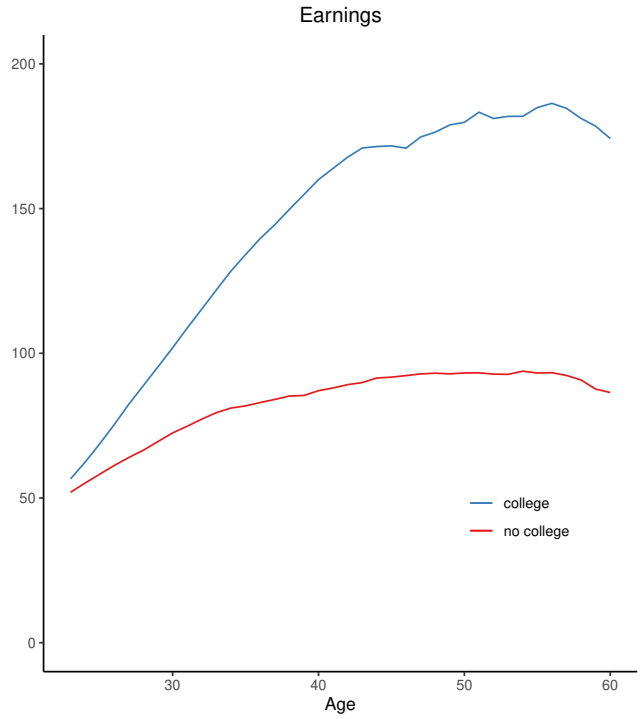


Figure 3: Earnings age profile by education: PSID

Earnings profiles differ by education attainment. Earnings profile for the college-educated workers is steeper and reaches a higher level at the end of the life cycle than that of high school-educated workers. Figure 3 is consistent with the heterogeneous income profiles reported by Guvenen (2009).

4.4 Intergenerational correlation of abilities

Using data from the NLSY79 and the NLSY79-Children and Young adults, I merge information from mothers and children to explore how cognitive abilities are transmitted across

generations. I use the AFQT percentile score as a measure of ability for parents and PIAT scores for children.

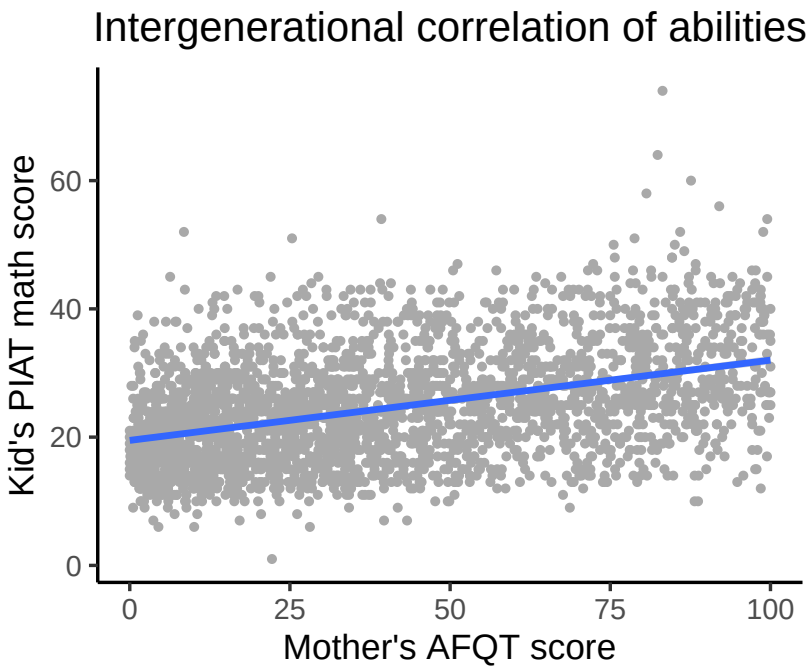


Figure 4: Intergenerational correlation of abilities, math scores

Figure (4) shows the relationship between mothers' AFQT scores and children's math PIAT scores. The correlation between mother's and children's ability is between 0.3 and 0.4, depending on whether I use math, reading recognition or reading comprehension as a measure of ability for children. This correlation is significant in all of these cases.

4.5 Intergenerational persistence of education

I compute several statistics on the persistence of education across generations. I consider waves from the PSID from 1974-2015 because there is enough information about the mother's and father's education. I focus on the group of 23-27 years old (25 years old bin).

I compute the probability of attending college, conditional on parental education. I condition in father's attending college, mother's attending college, and both parents college-educated. I repeat the exercise when parents do not go to college.

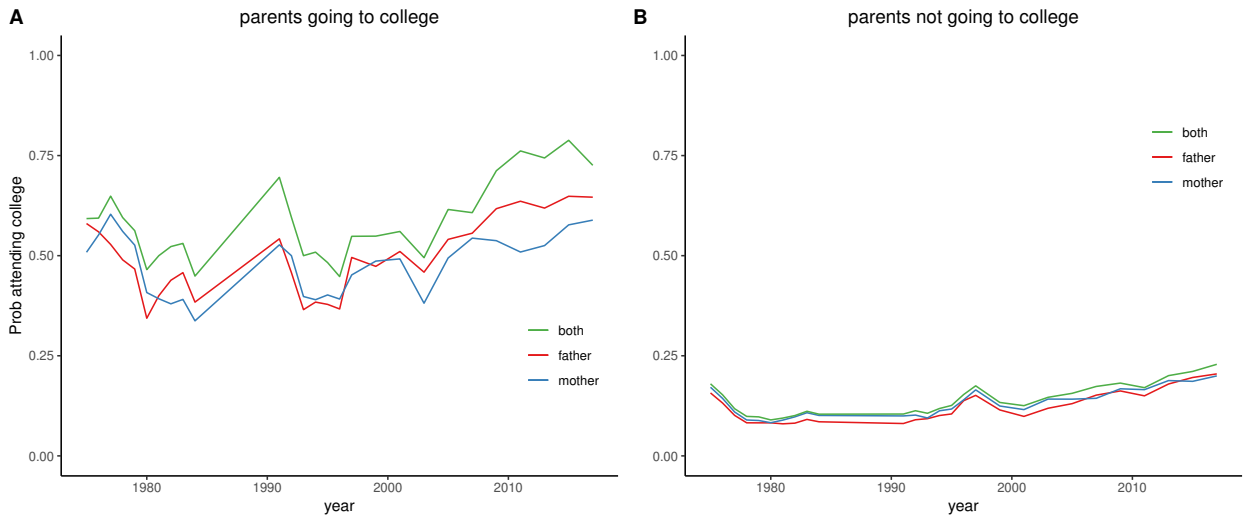


Figure 5: Probability of being college educated, conditional on parent's education

Figure 5 shows the probability of going to college conditional on parent's education. Panel A shows that conditional on both parents being college-educated, the probability of being college-educated is higher than the probability when only one parent went to college, for all years. Panel B shows conditional on both parents being non-college educated, the probability of being college-educated is also higher, although quantitatively small, than the probability when conditioning in only one parent being non-college educated. Both graphs display an upward trend, which represents an increase in enrollment in college education. There are not quantitatively important differences when doing the analysis by gender (shown in the appendix). On average, the probability of attending college conditional on parents being college educated is 0.5, and the probability when parents do not have a college education is 0.2.

4.6 Education by wealth class

In this section, I explore the conditional probability of attending college, given household wealth. Again, I focus on individuals aged 23-27. I constructed a measure of wealth class, according to the wealth distribution among those individuals. Each wealth class has the same size. Wealth classes 1, 2 and 3 correspond to the bottom, medium and upper side of the wealth distribution. I use wealth data from PSID, waves 1984,1989,1994, and the biannual waves from 1999 to 2015.

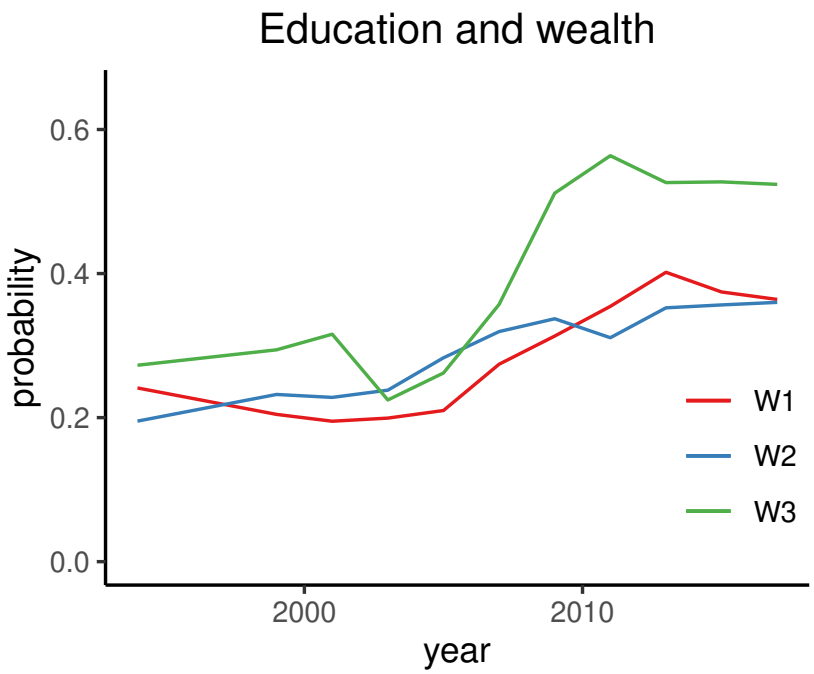


Figure 6: Probability of being college educated, conditional on household wealth

Figure 6 shows the probability of being college educated-conditional on wealth class. The probability of being college-educated conditional on being in the upper wealth class is higher for every year available. In recent years, the probability of attending college condition on being in the wealthy class has skyrocketed, from 27% in 1994 up to more than 50% in recent years, which suggest that wealth is more important to access to higher education in recent years. The conditional probability of going to college does not differ much for the bottom two wealth classes.

This analysis focuses on household wealth, and not on transferred wealth. At young ages, however, it is most likely that a great fraction of wealth corresponds to transferred wealth rather than self-made wealth. To better assess the contribution of transfers, in the next section I focus on whether the household has received gifts in recent years and its impact on education.

4.7 Education and parental transfers: Evidence from NLSY97

Because PSID lacks information on wealth transfers at young ages, I now use data from the National Longitudinal Survey of Youth, cohort 1997. The NLSY contains information on

young individuals aged 12-17 at the time of their first interview in 1997 (cohorts 1980-1984).

I focus on cohorts 1980 and 1981 because the information about transfers is more accurate and consistent across years[3]. I construct a variable with the sum of parental transfers to the child, excluding allowances, from ages 16 to 22.

Cohort	Q1	Median	Mean	Q3	Fraction Tr >0
1980	300	750	3493	2200	39.4%
1981	300	850	3292	2138	39.9%

Table 1: Descriptive statistics transfers

Table 1 shows some basic descriptive statistics about total transfers for cohorts 1980 and 1981. The histograms do not differ much. The distribution of transfer is extremely skewed, almost 40% receive no transfer, and the mean is more than three times the median. The maximum total transfer for each year is about 80,000.

[3]During the first years of the survey, respondents give information about transfers received from mother and father, separately. If they do not provide an exact number, they can give an estimate. This information is enough to construct a reasonable estimate of parental transfers during ages 16-22. For later cohorts, the survey changes slightly, and it is impossible to identify the sources of transfer (they asked from transfers from other relatives as well). The exact amount of transfer is also lost, and there are only estimates of transfers. Transfers for Cohorts 1980 and 1981 rely less on those estimates.

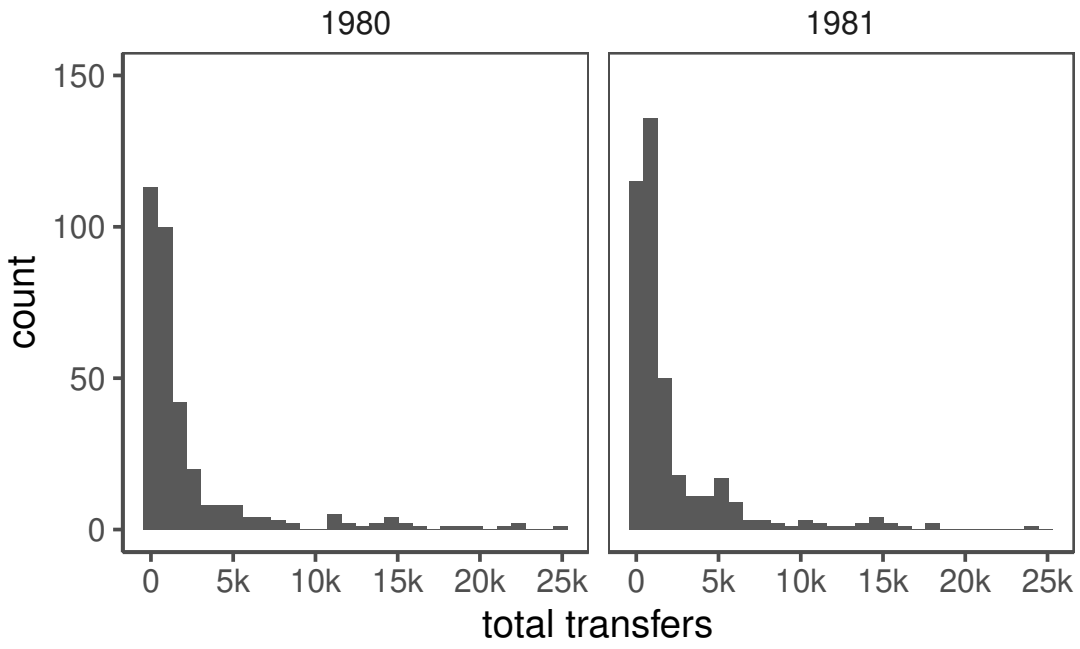


Figure 7: Histogram of positive total transfers

Figure 7 shows the histogram for positive transfers for both years. I trim the scale to display the histogram appropriately. The histogram displays a high positive skewness.

I estimate several specifications of a logit model to assess the importance of transfers in the likelihood of attending college. Since some amount of the total transfer is imputed, I also consider a dummy variable of whether the respondent received a transfer.

Table 2 summarizes the results of a logit probability model with a dummy variable of being college-educated as the independent variable. To control for transfers, I use either a continuous variable or dummy variable. I also control for demographic characteristics, income and wealth and parental education. In all specification total transfers is statistically significant at the 1 percent level. In the appendix, I show that I obtain similar results when I estimate a linear probability model.

Table 3 shows the average marginal effect of each of the previous models estimated. Models with continuous transfers suggest that the marginal contribution of transfers is around 3%. Models with a dummy variable for transfers suggest that the average marginal effect goes from 14% up to 22%. This means that, on average, there is roughly 20% extra chance of going to college for someone who received transfers, everything else constant.

	Dependent variable:							
	educ							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(1+transfer)	0.170***	0.165***	0.131***	0.150***				
	(0.015)	(0.015)	(0.017)	(0.020)				
log(family_income)			0.466***	0.303**			0.503***	0.338**
			(0.108)	(0.140)			(0.107)	(0.139)
family_wealth			0.003***	0.003***			0.003***	0.003***
			(0.0005)	(0.001)			(0.0005)	(0.001)
parents_educ				0.862***				0.882***
				(0.177)				(0.175)
dummy_transfer					1.019***	1.003***	0.762***	0.918***
					(0.104)	(0.105)	(0.121)	(0.141)
gender		✓	✓	✓		✓	✓	✓
race		✓	✓	✓		✓	✓	✓
Constant	−1.351***	−1.897***	−3.821***	−3.261***	−1.288***	−1.871***	−3.924***	−3.365***
	(0.072)	(0.175)	(0.418)	(0.582)	(0.073)	(0.174)	(0.416)	(0.580)
Observations	1,867	1,867	1,635	1,139	1,867	1,867	1,635	1,139
Log Likelihood	−1,076.209	−1,054.450	−848.941	−616.965	−1,096.043	−1,071.816	−857.855	−624.558
Akaike Inf. Crit.	2,156.417	2,120.900	1,713.882	1,251.930	2,196.087	2,155.632	1,731.709	1,267.116
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 2: Logit model

	Specifications							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AME	0.0331	0.0331	0.0331	0.0331	0.2169	0.2077	0.1402	0.1740

Table 3: Average Marginal Effects

5 Calibration and Model Fit

5.1 Model Parameters

Table 4 reports the parameters used in the solution of the model.

Parameter	Meaning	Value	Source/Target
		Prices	
r	rate of return	4%	calibrated
w_l	low wage	1	normalization
w_h	high wage	1.6	(Goldin and Katz (2007))
p	pension	40	40% of mean earnings
P_c	price of college	40	share college educated agents (30%)
		Preferences and human capital	
β	Discount Factor	0.95	Standard
σ	CRRA utility function	2	Standard
α	production function	0.5	HVY (2011)
γ	Parameter of Altruism	0.64	Share of zero transfers
δ	Human capital depreciation	0.03	(calibrated)
σ_z	Variance human capital shocks	0.136	(calibrated)
		Government	
μ	Tax constant	0.902	Guner et. al (2014)
τ	Tax progressivity	0.036	Guner et. al (2014)
τ_{ss}	Social security tax	0.106	HVT(2011)
		Distribution and Correlation of abilities	
m_θ	mean	0.85	mean profile
v_θ	variance	0.022	gini
ρ_θ	persistence	0.35	data

Table 4: Baseline Calibration

Prices. The interest rate is set to 4%. The wage for the low wage sector is normalized to 1. The wage in the high wage sector is set to 1.6, that is, there is a 60% skill premium, as

documented by Goldin and Katz (2007). The pension benefit and the price of college are calibrated to target a 40% replacement rate and a 30% of college-educated agents.

Preferences. The discount factor β is set to 0.95, a common value used in the literature for an annual discount factor. The risk aversion parameter σ is set to 2.

Human capital process and learning ability. The concavity of the human capital production function is set to 0.5, in line with estimates shown in the literature Huggett et al. (2011) and Guvenen et al. (2013). Human capital depreciation is set to 2%.

The parameters governing the process of learning ability are $\rho = 0.35$, as the correlation between mother's AFQT test and children's PIAT test in the NLSY[4]. The variance of abilities is set to match the inequality life-cycle pattern observed in the data.

Government policy. The tax schedule is taken from Guner et al. (2014) who show that the tax function in this paper is a good approximation of the US tax scheme. The social security tax rate is 10.6%, as in Huggett et al. (2011).

5.2 Model Fit

Figure 8 shows the income profile from the baseline model. It resembles the increasing and concave pattern observed in the data.

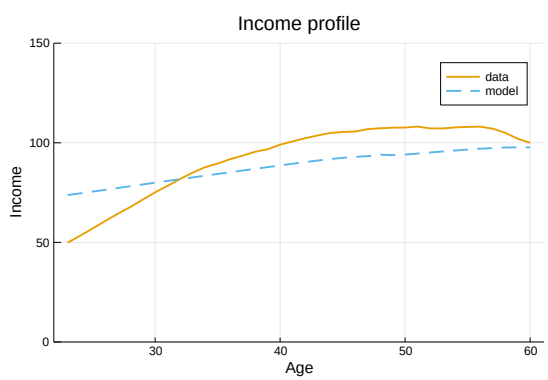
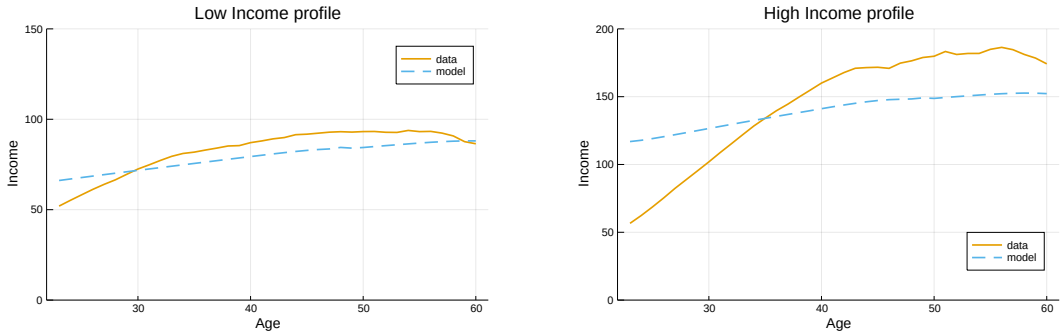


Figure 8: Model and Data: income profile

[4]Depending on the exact measure of kid's ability, the correlation is between 0.3 and 0.4



(a) low income profile

Figure 9: Model and Data: profiles

Figure 9 shows the income profile by education groups. It shows a similar pattern as Figure 3.

Figure 10 shows the evolution of the Gini coefficient over the life cycle. It displays a small increase over the life cycle, as suggested by the time effect Gini estimates shown in 2. The level is lower than the data.

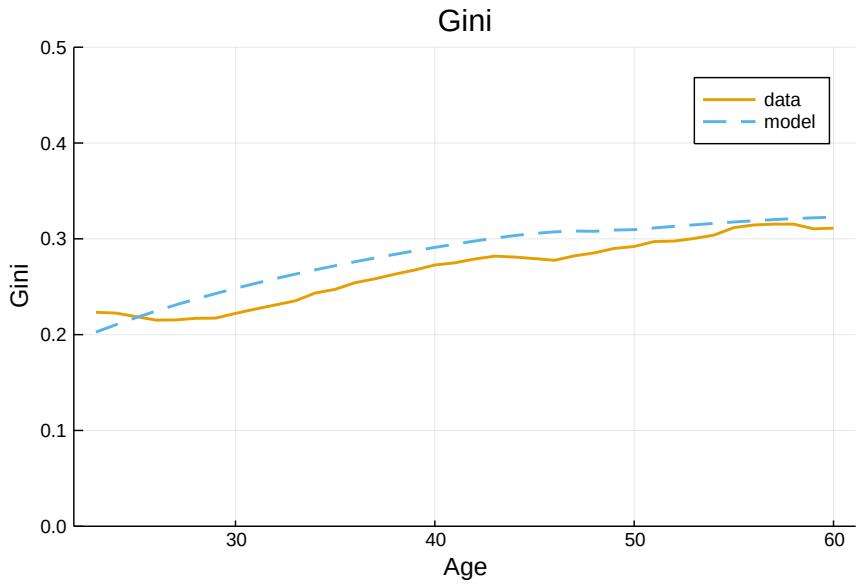


Figure 10: Cohort Gini index over the life cycle

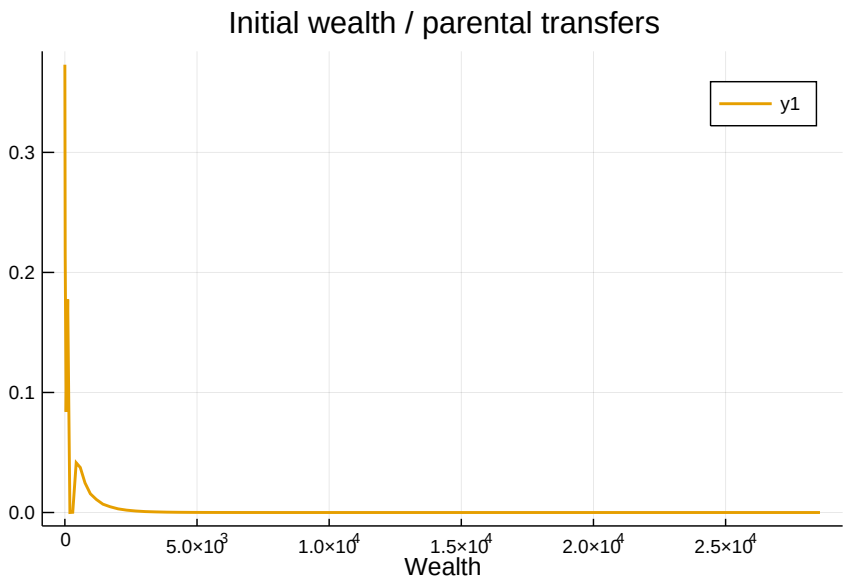


Figure 11: Initial wealth - parental transfers

Figure 11 shows the initial wealth distribution generated by the model. It is highly skewed consistent with the empirical evidence. 51% of agents receive positive transfers. This is close to the empirical observation of 40%. The fraction of college-educated agents in the model is 45%.

Moment	Target	Model
$P(\text{college}\|\text{no college})$	0.2	0.05
$P(\text{college}\|\text{college})$	0.5	0.38
replacement rate	0.4	0.45
share of college students	0.3	0.15
share of agents with zero transfers	0.6	0.37
β intergenerational income elasticity	0.4	0.43

Table 5: Model Fit

Table 5 shows other moments of the model.

6 Analysis

6.1 Sources of Lifetime Inequality

In this section I compare the present discounted value of income, wealth and utility[5] by changing 1) the level initial wealth, 2) innate ability. I compare with the 25th and 75th percentile with respect to the median in the ability and wealth distribution, keeping one dimension fixed at a time. Table 6 summarizes the findings.

(a, θ)	Lifetime utility	Lifetime earnings	Lifetime wealth
(a_m, θ_l)	-7.37%	-14.57%	-14.5%
(a_m, θ_h)	10.48%	20.13 %	20.03%
(a_l, θ_m)	-1.32%	-1.03%	-1.51%
(a_h, θ_m)	8 %	1.39 %	6.01%

Table 6: Lifetime Inequality

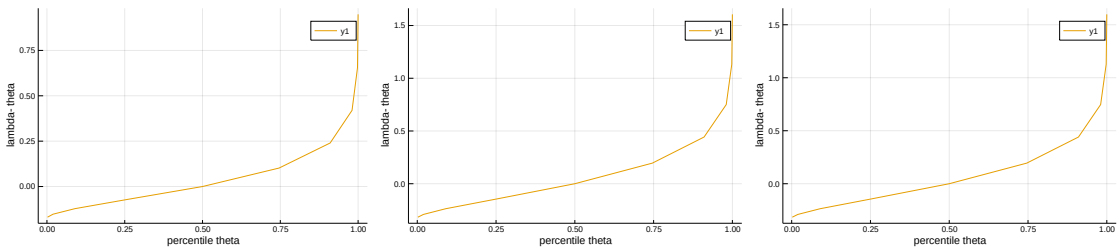
Table 6 shows the changes in lifetime utility, earnings and wealth when there is a change in initial conditions. Changes in wealth and in initial human capital have a great impact on lifetime welfare. The effect of ability is lower. These results are in stark contrast with Huggett et al. (2011), who argue that among initial conditions, ability and human capital have a great impact and that of initial wealth was almost negligible. There are two reasons that explain the different findings. First, they do not tale into account that financial wealth is necessary to acquire specific human capital. For some agents, have a small extra human capital has a big impact since they are now able to go to college. Second, they do not consider borrowing constraints. In the baseline model, agents are not allowed to borrow to attend education. In the next section, I explore the effect of having different borrowing constraints on lifetime welfare.

To get a better understanding of how initial conditions matter, I plot the changes in utility, earnings and wealth as we move along the ability and wealth distributions. Figure 12 shows how different measures of welfare change, the presented discounted value of utility, income and wealth, as we move along the distribution of abilities, in comparison to the mean values of each one of these measures of welfare. By construction, each graph

[5]Utility changes are expressed as consumption equivalent variations

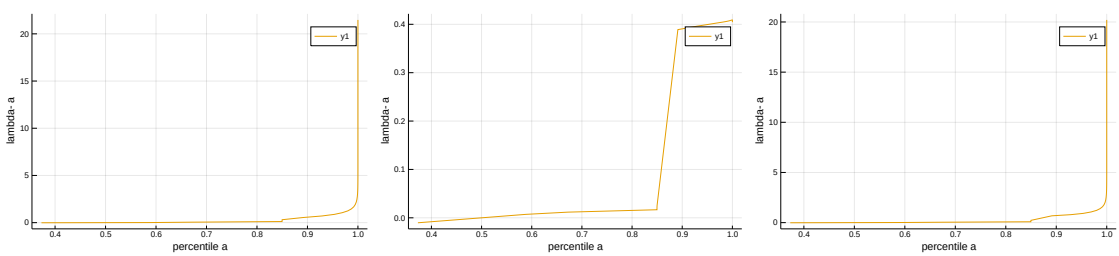
crosses the y-axis at 0 at the median of the distribution. They all show a similar pattern, as we move high along the distribution, the utility is increasing and has a convex shape at the very left end.

Figure 13 shows the result of the same exercise as in Figure 12, but using the distribution of initial wealth. Welfare gains increase much more at the top of the distribution. In terms of income, the discontinuity is due to the fact that near that level of wealth, most agents decide to go to college, and then they get a higher wage per unit of human capital.



(a) Utility (b) Income (c) Wealth

Figure 12: Change in utility, earnings and wealth as function of ability



(a) Utility (b) Income (c) Wealth

Figure 13: Change in utility, earnings and wealth as function of initial wealth

6.2 Variance decomposition

In this section, I want to study the variance decomposition of lifetime income, lifetime wealth and lifetime utility. I want to decompose the variance in two: variance associated with differences in initial condition vs variance associated with differences in shocks received during the lifetime.

For a variable Y (lifetime income, lifetime wealth, lifetime utility), I can use the following decomposition

$$\text{var}(Y) = \underbrace{\mathbb{E}(\text{var}(Y|X))}_{\text{due to shocks}} + \underbrace{\text{var}(\mathbb{E}(Y|X))}_{\text{due to initial conditions}} \tag{3}$$

where X is a vector of initial conditions. In the appendix, I show how to compute each of these terms in a dynamic programming problem.

Y	percentage of variance due to initial conditions
Lifetime income	7.47%
Lifetime wealth	11.59%
Lifetime utility	4.63%

Table 7: Variance decomposition

Table 7 shows the fraction of variance in lifetime utility, lifetime earnings and lifetime wealth associated with initial conditions. Approximately 10% of the variance in lifetime earnings and lifetime utility is explained by variation in initial conditions, whereas initial conditions explain up to 15% of lifetime wealth.

6.3 Social Mobility

Empirical studies on social mobility have focused on estimating equations of the form

$$\log(Y_{n+1}) = \alpha + \beta \log(Y_n) + \varepsilon_{n+1} \tag{4}$$

where Y_n is a measure of the permanent income of agents in generation n. Black and Devereux (2011) and Solon (2014) provide a theoretical foundation for this specification as well as practical difficulties in estimating it. The parameter β is known as intergenerational elasticity and $(1 - \beta)$ is a measure of mobility. The calibrated model delivers an estimate of the intergenerational income elasticity of 0.4, in line with empirical studies.

6.4 Quantitative exercises

In this section, I explore the impact of (i) initial wealth, (ii) correlation of abilities, (iii) the rise of college tuition and (iv) skill-biased technical change.

I show how (i)-(iv) impact income profiles and Gini coefficients. Then I compute the variance decomposition as in Table 7 for each one of these cases. The variance decomposition changes because there are changes in values (Y variables, value functions) but also there are changes in steady-state distributions. To isolate each of these effects, I compute the variance decomposition under the new steady-state distribution and also under the original distribution.

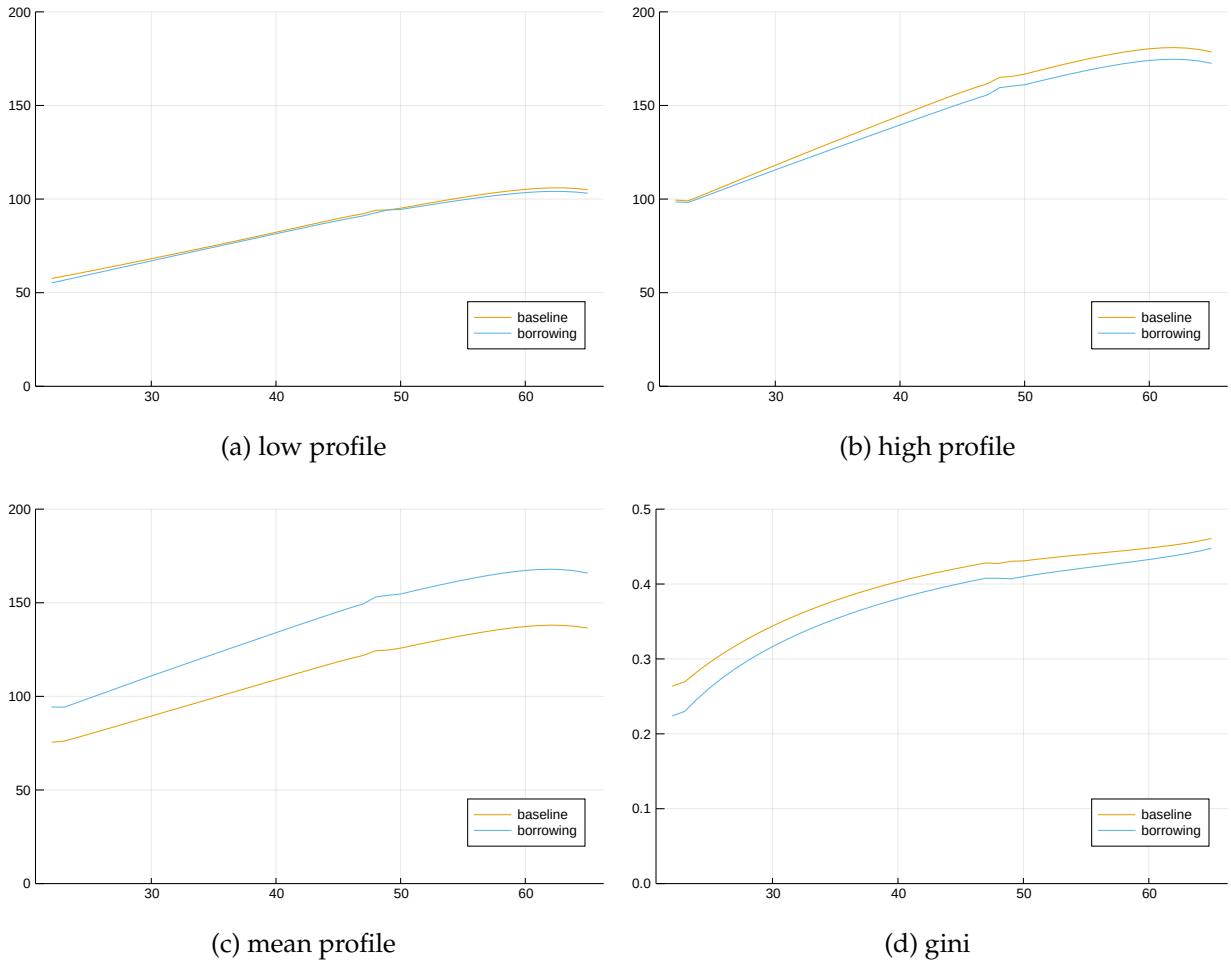
variables	baseline	borrowing	ability	college	sbtc
P0	0.03	0.08	0.04	0.01	0.03
P1	0.38	0.45	0.37	0.31	0.38
share college	0.15	0.28	0.16	0.06	0.15
zero wealth agents	0.37	0	0.37	0.39	0.4
β	0.43	0.43	0.18	0.41	0.43

Table 8: Moments

6.4.1 The effect of initial wealth and borrowing constraints

In this section, I show the importance to access capital markets. I replicate the analysis of sections 6.1 and 6.2 with a loose borrowing constraint. More specifically, I allow agents to borrow as much as they need to pay for college, but not more than that.

Figure 14 shows income profile for high school graduate and college graduate as well as average income profile. Low and high skill profiles decrease slightly, but college enrollment increases substantially. As a result, the mean profile increases. Agents are more likely to attend college, and this effect is stronger for agents whose parents did not attend college. There is an increase in income mobility and a decrease in Gini coefficients.



(a) low profile

(b) high profile

(c) mean profile

(d) gini

Figure 14: Earnings profiles and gini: Borrowing constraints

Y	% of variance due to initial conditions (baseline)	% variance due to initial conditions g^{old}	% variance due to initial conditions g^{new}
Lifetime income	7.47 %	7.49 %	7.49%
Lifetime wealth	11.59%	12.28%	12.28%
Lifetime utility	4.63%	5.12%	5.12%

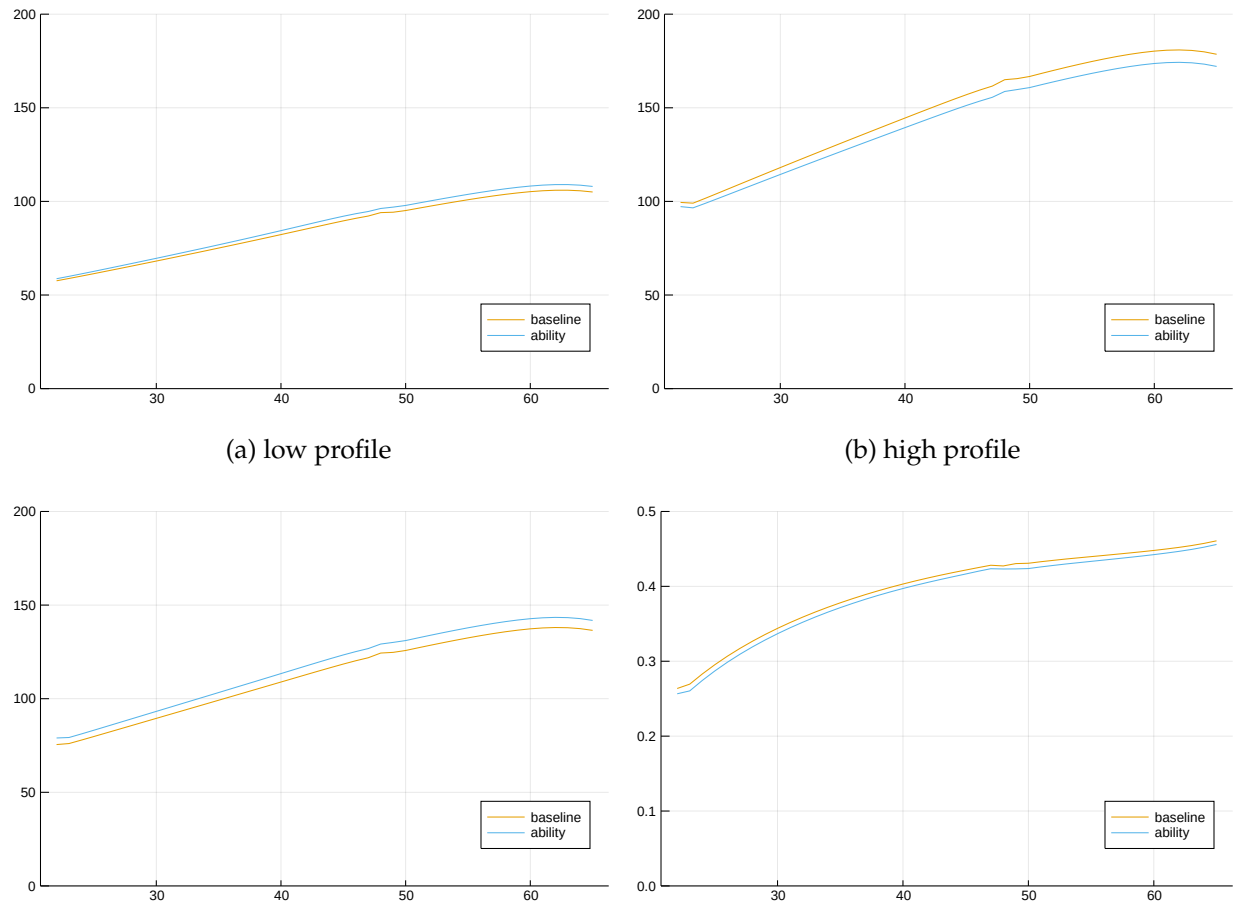
Table 9: Variance decomposition

Table 9 shows the variance decomposition of the economy with better access to credit. Even though this economy displays higher mobility and lower inequality, initial conditions explain roughly the same fraction of variance as in the baseline case.

6.4.2 The effect of parental background and correlation of abilities

The literature on income mobility has shown that income is correlated across generations. In this model, there is a correlation of income across generations for several reasons: (i) parental transfers allow agents to go to college, which allows parents are children to make similar decisions regarding education, and (ii) correlation of innate abilities across generations.

To study the effect of intergenerational correlation of abilities, I shut down the effect of correlated abilities, i.e., I set $\rho_\theta = 0$. Then I simulate the model and perform the same exercise as in sections 6.1 and 6.2



(a) low profile

(b) high profile

(c) mean profile

(d) gini

Figure 15: Earnings profiles and gini: No correlation of abilities

Figure 15 shows income profiles and the evolution of Gini coefficients. The effect of accounting for the intergenerational correlation of abilities is small. As abilities are no

longer correlated, there is a sharp increase in mobility, kids of low and high ability parents have the same likelihood of being high ability.

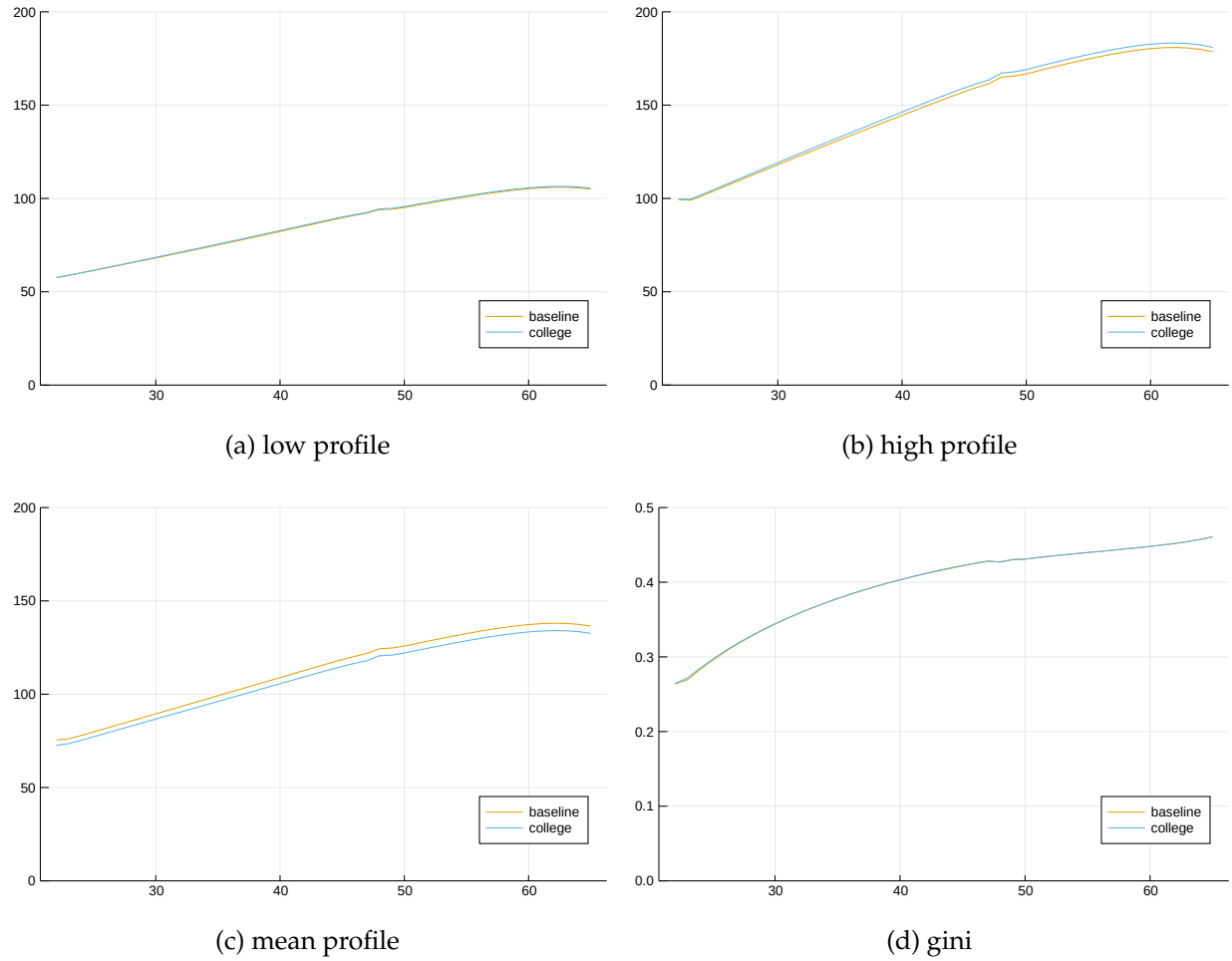
Y	% of variance due to initial conditions (baseline)	% variance due to initial conditions g^{old}	% variance due to initial conditions g^{new}
Lifetime income	7.47%	7.48%	6.89%
Lifetime wealth	11.59%	11.59%	10.59%
Lifetime utility	4.63%	4.61%	4.45%

Table 10: Variance decomposition

Table 10 shows that once the channel of intergenerational correlation of abilities is shut down, initial conditions matter slightly less for lifetime income and wealth. This is due to the fact that the steady-state distribution changes. Keeping the distribution constant, there is an increase in the variance explained by initial conditions. This is due to the fact that in the original distribution initial wealth and parental ability are correlated and furthermore ability is correlated across generations, high ability parents save more to transfer more to descendants because they are likely to have higher ability as well. As a result, initial conditions can explain a larger variation of welfare in the life cycle. In the new steady-state distribution, abilities and wealth are less correlated, and thus they explain a lower fraction of variation in lifetime welfare.

6.4.3 The increase in college tuition

In the past decades, there has been a sharp increase in college tuition. This section analyzes how the increase in tuition impacts income, wealth and welfare.



(a) low profile

(b) high profile

(c) mean profile

(d) gini

Figure 16: Earnings profiles and gini: Increase in college tuition

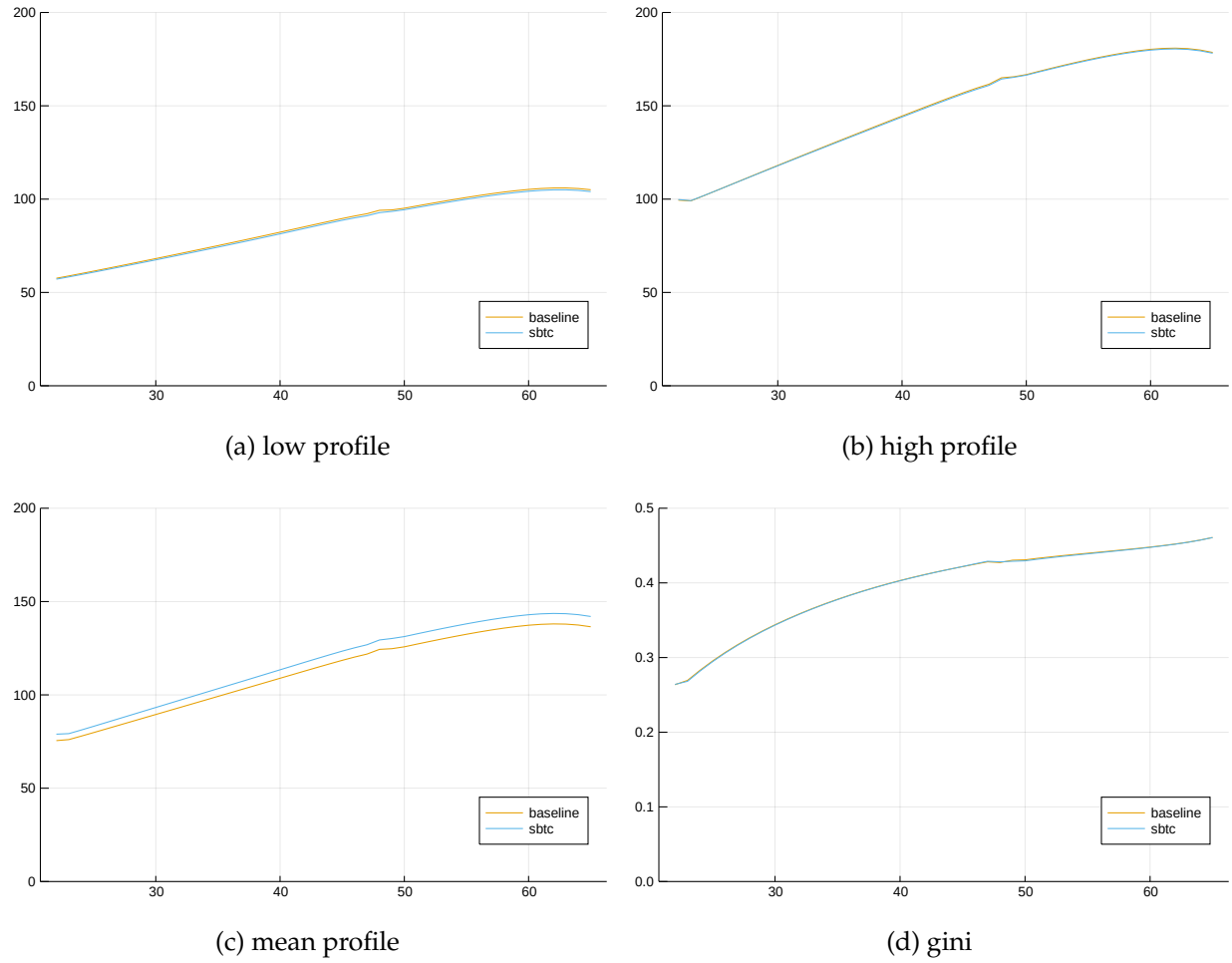
Figure 16 shows profiles and Gini coefficients when college tuition increases by 50%. College enrollment decreases. The measure of agents with zero wealth increases since more agents will not attend college and thus they do not as much wealth. Gini coefficients are almost identical.

Y	% of variance due to initial conditions (baseline)	% variance due to initial conditions g^{old}	% variance due to initial conditions g^{new}
Lifetime income	7.47%	7.46%	6.67%
Lifetime wealth	11.59%	11.57%	10.12%
Lifetime utility	4.63%	4.38%	3.67%

Table 11: Variance decomposition

The fraction of initial income and wealth explained by initial conditions is roughly the same as in the baseline model.

6.4.4 Skill biased technical change



(a) low profile

(b) high profile

(c) mean profile

(d) gini

Figure 17: Earnings profiles and gini: Skill-biased technical change

Figure 17 shows profiles and Gini coefficients.

Y	% of variance due to initial conditions (baseline)	% variance due to initial conditions g^{old}	% variance due to initial conditions g^{new}
Lifetime income	7.47%	7.48%	7.48%
Lifetime wealth	11.59%	11.59%	11.59%
Lifetime utility	4.63%	4.63%	4.63%

Table 12: Variance decomposition

The variation explained by initial conditions is roughly the same as in the baseline model.

7 Conclusions and Final Remarks

The human capital theory is capable to explain several facts about the observed cross-sectional inequality: earnings profiles and Gini coefficients. However, to accurately assess the importance of initial conditions in explaining lifetime welfare, several ingredients are missing in this theory. This paper aims to fill that gap, considering a model with intergenerational links and costly human capital accumulation.

Using PSID data I show the evolution of mean earnings and earnings by educational group, as well as the evolution of Gini coefficients conditional on age. Using data from the PSID and NLSY, I show evidence on the importance of wealth and parental transfers to attend college, and how abilities and educational decisions are correlated across generations.

I propose a model with intergenerational links, in terms of abilities and transfers of wealth, in which agents can choose to attend college provided that they have enough resources. Borrowing limits hinder optimal human capital accumulation. Agents would like to accumulate human capital, but they need consumption too. Since they do not have enough wealth, they accumulate less to consume today, which has long-lasting effects. Furthermore, poor agents can't attend college which also impacts their lifetime earnings. As a result, differences in initial conditions are capable to explain part of the cohort lifetime inequality.

Overall, initial conditions matter and the effect abilities seem more important than the effect of parental wealth. In terms of lifetime utility, earnings and wealth, deviations

around the ability distributions are more important than deviations around the wealth distribution. Initial conditions explain roughly 10% of the variance in welfare. Improving access to credit decreases inequality by increasing the amount of college-educated agents. More than half of the intergenerational income elasticity is explained by correlation of abilities across generations, and the rest by shocks received in the life cycle.

In this paper, the role of financial wealth is through human capital accumulation. Another way in which financial wealth might influence is through inheritances. Although not explicitly modeled in this paper, inherited wealth helps to increase consumption level and smooth its fluctuations against income or human capital shocks. In this regard, inheritances work similarly to transferred wealth not used in human capital accumulation in the model. Several authors have emphasized the role of inheritance in determining observed inequality, such as De Nardi (2004) and Piketty (2014). The role of inheritance is left for future research.

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A More on Empirical Evidence

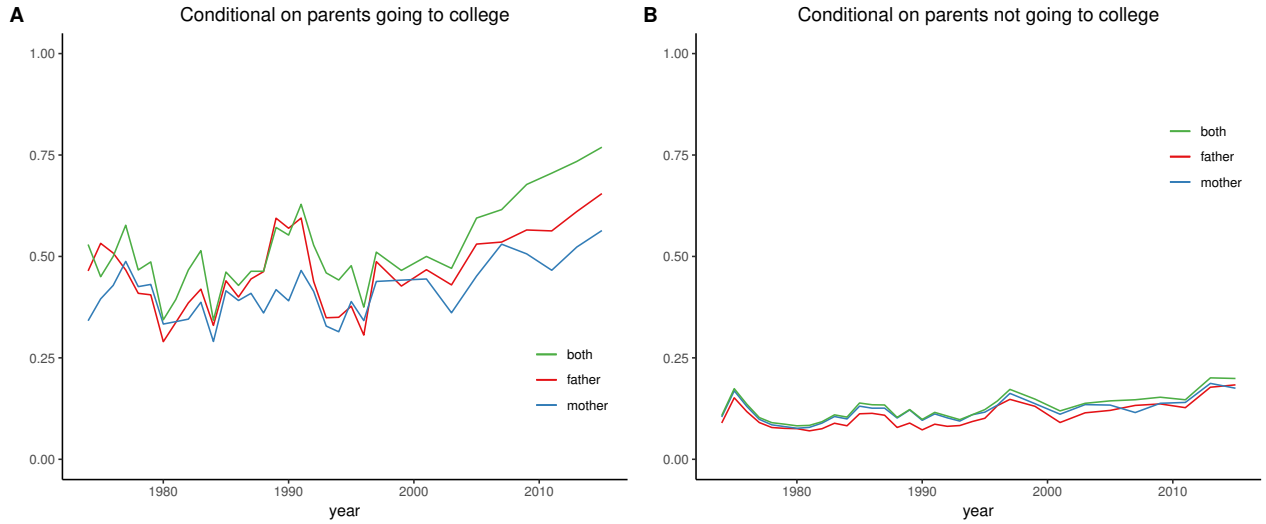

Figure 18: Probability of being college educated, conditional on parent's education: male sample

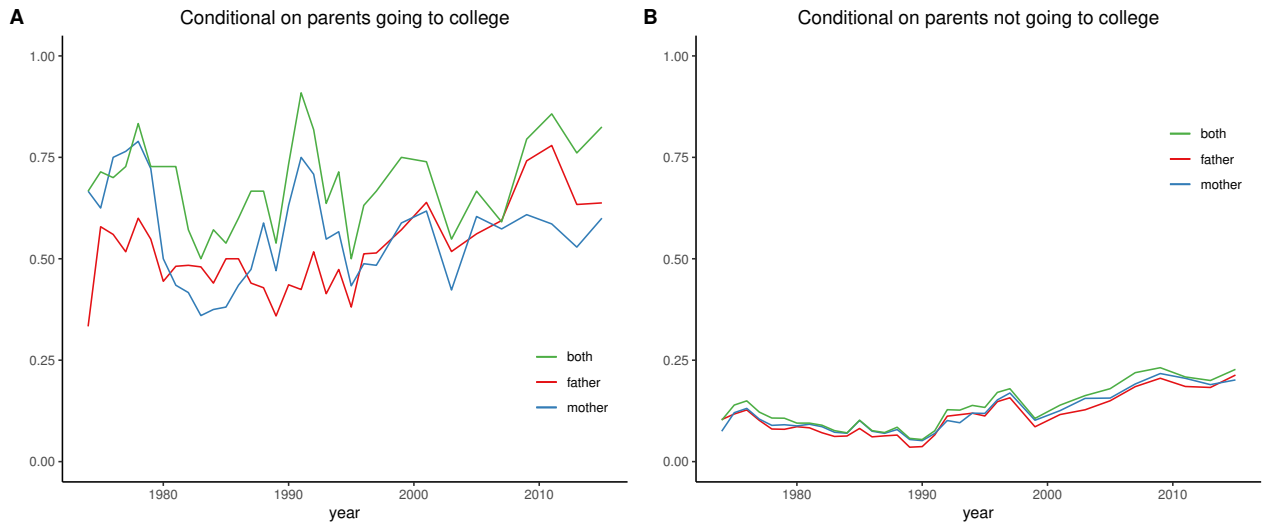

Figure 19: Probability of being college educated, conditional on parent's education: female sample

Figures 18 and 19 show the probability of attending college conditional on parents education for two separate subsample, men and women. The overall pattern is that conditioning on both parent being college educated, there is more likely to be college educated. Women series look more volatile.

First, I construct several contingency table showing the proportion of agents going to college conditional on receiving a transfer of at least $500 during those ages. Then I run a linear probability model. The results of the logit model as shown in the main text.

Cohort	No transfer	Transfer
1980	0.22	0.56
1981	0.24	0.52
1982	0.25	0.50
1983	0.25	0.48
1984	0.28	0.44

Table 13: Probability of going to college conditional on transfer

Table 13 shows that the probability of attending college is higher for individuals who received parental transfers during ages 16-22.

Table 2 shows the results of a logit model. As in Table 14, all specifications show that

	Dependent variable:							
	educ							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(1 + total_transfer)	0.037***	0.035***	0.026***	0.029***				
	(0.003)	(0.003)	(0.003)	(0.004)				
gender		0.083***	0.104***	0.107***		0.091***	0.109***	0.115***
		(0.020)	(0.021)	(0.025)		(0.021)	(0.021)	(0.026)
race		0.041***	0.015	0.016		0.043***	0.014	0.015
		(0.009)	(0.010)	(0.013)		(0.009)	(0.010)	(0.014)
log(fam_income)			0.070***	0.057**			0.077***	0.063**
			(0.017)	(0.024)			(0.017)	(0.025)
fam_wealth			0.001***	0.001***			0.001***	0.001***
			(0.0001)	(0.0001)			(0.0001)	(0.0001)
college_res_p				0.175***				0.183***
				(0.034)				(0.034)
received					0.217***	0.208***	0.144***	0.177***
					(0.021)	(0.021)	(0.022)	(0.026)
Constant	0.205***	−0.053	−0.314***	−0.316***	0.216***	−0.060	−0.338***	−0.345***
	(0.013)	(0.045)	(0.070)	(0.105)	(0.013)	(0.045)	(0.070)	(0.106)
Observations	1,867	1,867	1,635	1,139	1,867	1,867	1,635	1,139

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: Linear probability model

the amount of transfers are statistically significant.

B Variance decomposition in Dynamic Programming

In a general problem, the present discounted value of utility can be written as

$$B = \sum_{t=0}^{T} \beta^t u(x_t) \tag{5}$$

where x_t is the state at time t, which may follow a Markov process. The value function is define as the sum of expected discounted future pay offs, given the initial state x

$$J(x) = \mathbb{E}(B|x_0 = x) \tag{6}$$

It is useful to define the following operator

$$M(x) = \mathbb{E}(B^2|x_0 = x) \tag{7}$$

Notice that $J(x)$ and $M(x)$ can be written as

$$J(x) = u(x) + \beta P(x'|x)J(x') \tag{8}$$

$$M(x) = u(x)^2 + 2\beta u(x)P(x'|x)J(x') + \beta^2 P(x'|x)M(x') \tag{9}$$

The previous two equations can be computed recursively. Using $J(x)$ and $M(x)$ we can compute the variance decomposition of a variable

$$\text{Var}(Y|x) = \mathbb{E}(Y^2|x) - \mathbb{E}(Y|x)^2 = M(x) - J(x)^2 \tag{10}$$

To compute the variance decomposition, I use

$$\text{Var}(Y) = \mathbb{E}(\text{Var}(Y|x)) + \text{Var}(\mathbb{E}(Y|x)) \tag{11}$$

The first term on the right hand side are computed using $M(x)$ and $J(x)$ and the initial distribution over states $g(a, h, \theta)$. The second term on the right hand side is computed using the value function and the initial distribution over states.

C Numerical Solution

Grids I define grids for ability θ, human capital h and financial capital a. The model is solve using parallel computation in the θ dimension.

Function approximation Policy and value functions are solved using collocation methods. I solved the model in the collocation nodes and I interpolate between nodes. I use linear interpolation.

Optimization problem The problem is solved using backward induction. At each t, the optimization problem is solved using golden search method for one dimensional problem (e.g. during retirement), using a two-dimensional golden method for two-dimensional problems (e.g. during working periods) and a nested golden search for s and a bivariate numerical solver for savings and transfer (to solve for inter-vivos transfers). This last piece is by far the most challenging and computationally expensive part of the algorithm. Even though the model is finite horizon, I need to solve for the child's value function. Since I focus on stationary equilibrium, I iterate until value function converges.

Distributions Given the discretization of the state space, the policy functions and exogenous shocks define transition matrices over states. The steady state of the model is computed as the ergodic distribution of the transition matrices of the model. In the literature this technique is known as non-stochastic simulations.