Unequal opportunities, innovation, and redistributive taxation

Burak Ünveren

Yıldız Technical University

Abstract: This study analyzes how redistributive taxation would affect the interaction between inequality of opportunity and economic growth. To answer this question, we develop a dynamic model where parental income determines the initial abilities of the children. Given their initial abilities, the children make optimal college choices before entering the labor market as employees. If the employees possess more human capital, then the rate of economic growth increases due to higher R&D investment by the firms in pursuit of profits. This intergenerational model with endogenous growth is estimated with longitudinal US data from 1999 to 2017. Based on our estimations, we simulate certain redistributive policies. A universal basic income program financed by higher sales taxes yields the strongest impact on human capital accumulation with a substantial positive effect on innovation and economic growth. Policies that compensate the adults affected by unequal opportunities during childhood also have positive, albeit remarkably weaker, impacts.

Keywords: Intergenerational income distribution, innovation, redistribution

JEL: E24, O30, H2

1. Introduction

Can progressive redistributive taxation policies boost economic growth by increasing human capital investments? It may be reasonably argued that poor families, who are elevated to the middle class by virtue of redistribution, would have more time and money to invest in their children's education. This mechanism with potentially positive outcomes can be called the income effect. Indeed, Acemoğlu and Pischke (2001) find that a 10% increase in family income corresponds to 1.4% increase in probability of attending college.[1] The other side of the coin can be called the substitution effect with unambiguous negative effects. Progressive redistributive policies mean, by definition, the skill premium would be smaller, and the rate of return to education is lower. The substitution effect would unequivocally discourage education, schooling, and human capital accumulation in general.

To analyze the overall net impact of these two potentially opposing effects of redistribution (i.e. income and substitution effects) in empirical terms, we analyze an intergenerational model with education. The children have different levels of initial academic abilities depending on their family background: low, middle, and high income. These incomes groups have equal sizes so that each of them comprises 1/3rd of the economy. By comparing the life time wage differential (net of costs), each 18 year old chooses between going to college or not. College education raises human capital at a certain rate depending on family background. After making the college choice, individuals enter the labor market and supply labor optimally. Individuals can accumulate human capital while working through a mechanism called on-the-job-training until retirement. Upon retirement, survival becomes a probabilistic event. When an individual dies, her inheritance is left to the next generation. This life-cycle model consists of 68 periods (from 18 to 85 years old) and each period is a calendar year.

The model also involves endogenous economic growth based on a Schumpeterian approach. To be specific, the firms invest in R&D to increase the probability of developing a superior technology. The firm with the superior technology would reduce its marginal costs, gain a competitive edge, and thereby, enjoy a certain level of monopoly profit. This means that R&D

---

[1] Of course, if the transfers to the poor families are shouldered by the relatively affluent families, then the resources to be invested in education by the rich would decrease. But, theoretically, the overall net effect on education would still be positive if the elasticity estimated by Acemoğlu and Pischke (2001) is constant.

and long-run economic growth are spurred by the monopoly profit secured by technological advantage. But the available amount of human capital increases the monopoly profit. As a consequence, any economic policy that would raise the individuals' human capital accumulation would also raise the rate of innovation and growth.

Our modelling approach is an extension of Roemer and Ünveren (2017) which is a theoretical analysis of economic status transmission in an intergenerational framework with two-period life-cycles. Becker and Tomes (1986) is an early influential example of two-period models. In comparison, we study a multi-period model with labor supply, human capital accumulation, innovation, retirement, and inheritance. A recent example of a richer version of Becker and Tomes (1986) is Lee and Seshadri (2019) whose equilibrium predictions successfully match with the empirically observed intergenerational elasticities of income earnings. A similar example of an estimated OLG model with elaborate details is Abbott et. al. (2018). For the sake of accessibility, however, we formalize a different model that can be seen as an extended version of Heckman et. al. (1998) and Fan et. al. (2017) by incorporating parental background and intergenerational transmission of income inequality. A related but different concept is the intergenerational transmission of wealth, which is analyzed by De Nardi and Yang (2016), De Nardi and Fella (2017), and Cagetti and De Nardi (2008). These studies, however, do not take into account at least one of following concepts: R&D (innovation), labor supply and schooling choice over the life-cycle.

The parameters of our life-cycle model are estimated using the longitudinal PSID data from 1999 to 2017. The data includes micro-level information on consumption, labor supply, and wealth from the US. We use the non-linear least squares method invoking the optimality conditions of individuals for estimation purposes. As expected, the estimates indicate that the children raised in more affluent families (i.e. top 33.3%) go to better and more costly colleges. They also have higher levels of wealth at the beginning of their professional careers when they enter the job market. Therefore, in comparison, less privileged kids start their adult lives with less favorable initial conditions in terms of wealth and human capital.

The estimated parameters are also used to calibrate the parameters of technology. Then we simulate the model under three different redistributive policy experiments. Our major focus is on how human capital accumulation decisions would react to these policies. The relevance of human capital stems from the fact that it is the key variable for the motivation of firms to invest in R&D.

Our guiding principle for policy design is the equality of opportunity ethos that commands compensation for factors individuals cannot be responsible for. So the first two redistributive policy experiments compensate adults who were raised by low-income parents. To this end, all adults pay the same lump-sum tax and the tax revenues are transferred to adults who come from low-income families. These two policy experiments satisfy the equality of opportunity principle as no one can be held responsible for the low income of their parents. The potential efficiency benefit of these policies would be weakening the persistence of economic status over generations.

In the first policy experiment, the transfer payments are lump-sum: $1K per annum. In the second policy experiment, transfer payments depend on wage income so that we can see the role of the distortionary impact of transfers. For example, the rate of transfer is 25% if the wage income of an adult is $14K wage and it gradually decreases as income increases. Eventually, the rate of transfer reaches to 0% for income more than or equal to $32K. Both of these policies induce a very small but positive increase in innovation and economic growth due to marginal improvements in human capital accumulation. The reason behind this small effect is that different socio-economic groups are impacted in opposite directions, reducing the net effect in a substantial way.

A redistributive policy, however, does not necessarily need parental income data to alleviate inequality of opportunity. The primary example is the universal basic income program which we discuss as our third policy experiment. In this policy experiment, we assume that everyone receives $850 unconditional income and this is financed through increasing the sales taxes by

3%. In this case, the college enrollment rates of children from all backgrounds significantly increase. Therefore, the effect on R&D and long-run growth is positive and sizeable. So universal basic income policy induces the highest positive effect on economic growth and technical change.

Marrero and Rodríguez (2013) present empirical evidence for a robust and significant positive relationship between equality of opportunity and economic growth. The idea that unequal opportunities prevent growth while increasing overall inequality is also emphasized by Dabla-Norris (2015) to explain the negative empirical relationship between Gini coefficients and economic growth. These empirical analyses, however, take equality of opportunity and income inequality as exogenous variables parametrized by the Theil index, the generational elasticity of income, and the Gini coefficient. Instead, the level of equality of opportunity and income inequality in our model are endogenous, and hence, relevant economic policies are required for enhancing equality. Therefore, due to the optimal reactions of individuals to these policies, our results yield more nuanced outcomes– a feature that we find more realistic and interesting. For example, the policies that stipulate transfers to people from low-income families make almost no change in growth in our simulations. However, the universal basic income program induces a significant increase in economic growth. Presumably, there would be very different outcomes if we considered subsidies for investment in educational or entrepreneurial activities. The standard econometric studies would, however, fail to compare any alternative policies in counterfactual scenarios due to lack of optimizing behavior in their empirical strategies.

This brings us to the contributions of our study. To the best of our knowledge, we present the first dynamic analysis of how redistributive policies affect investment in R&D. For example, the most similar study to ours is Lee and Seshadri (2019) which analyzes the intergenerational transmission of economic status in a very rich OLG framework. However, their study does not analyze how redistributive policies affect equilibrium. Moreover, the labor supply is absent in their model 12 period model. Another similar study is Abbott et. al. (2018) which studies the impact of education policies in an OLG framework. Although their model involves labor supply, investing in human capital after college is excluded. In contrast, our model involves human capital accumulation by the employees over their life-cycles. According to our estimates, this is a crucial aspect of the inequality between workers with and without a college degree. But most importantly other studies do not discuss how inequality of opportunity is related to innovation/technology (see also Keane and Roemer (2009)). This question is considered by Galor (2011) and Galor and Tsiddon (1997). It is noteworthy that these studies exclude optimal R&D investments from their analyses. They use a rather mechanical modelling approach where human capital externalities automatically create growth. Moreover, these studies also treat inequality of income as an exogenous parameter akin to the empirical studies in the field. In real life, however, inequality of income and opportunity are endogenous economic outcomes, produced by the actual decisions of individuals, firms, and the government.

The paper is organized as follows. The next section presents the theoretical life-cycle model. Section 3 discusses innovation and technology. The data and the estimation techniques are presented in Section 4 and 5. The results are is discussed in Section 6. The redistributive policies are analyzed in Section 7. Finally, Section 8 concludes.

2. The model

Let us analyze a dynamic economy with heterogeneous individuals with different family backgrounds, education, initial ability and initial wealth levels. Each individual has a certain parental background: low, middle, and high income, denoted by $J = L, M, H$.[2] The initial ability of J parent's child is a random variable H^J distributed as $H^J \sim \Gamma\left(\alpha_1^J, \alpha_2^J\right)$ denoting the gamma distribution.[3] Note that the parameters of the distribution $\Gamma\left(\alpha_1^J, \alpha_2^J\right)$ depend on the family

[2] Given the other continuous variables, discretizing parental income helps us to avoid the curse of dimensionality. This problem becomes an issue when we use high order Chebyshev polynomials to approximate optimal behavior. We are inspired by the empirical strategy of Panel Study of Income Dynamics (PSID) which collects parental income data as low, middle, and high income.

[3] We prefer to use the gamma distribution as it provides more geometric flexibility compared to its most obvious alternative, log-normal distribution.

background $J = L, M, H$. At the age of 18, each individual learns the true level of her initial ability. After learning the level of initial ability, each individual makes a schooling choice denoted by S. If the individual does not choose to go to college, then we write $S = 0$. Otherwise, $S = 1$ which means some college education, or more. If the individual does not have some college education ($S = 0$), then the individual starts working at age $a_0 = 19$. If the individual has some college education ($S = 1$), then the individual starts working at age $a_0 = 23$. This particular lag in labor market participation due to college education is a major component of the alternative cost of schooling. All individuals are assumed to make their schooling decisions optimally by comparing the costs and benefits of a college degree at age 18. For the time being, however, let us consider an individual who already made this choice.

The initial ability, family background, and schooling choice determine the initial human capital. Write $H_a^{S,J}$ for the level of human capital of an individual with schooling choice S from a J type family at age a. If $S = 1$, then the college education boosts initial ability by a certain factor ρ^J which determines the initial human capital as $H_{23}^{1,J} = (1 + \rho^J)H^J$. Recall that college graduates enter the labor market at the age of 23. We call ρ^J the rate of return of college education. If $S = 0$, then, due to lack of any college education, the initial ability is directly transformed into initial human capital, $H_{19}^{0,J} = H^J$. Again, individuals with no-college education start working at the age of 19.

The time invested in human capital is $I_a^{S,J} \in [0,1]$. The human capital accumulates according to the following law of motion:

$$H_{a+1}^{S,J} = A_s\left(I_a^{S,J}\right)^{a_s}\left(H_a^{S,J}\right)^{b_s} + (1 - \sigma)H_a^{S,J} \tag{1}$$

where $\sigma \in (0,1)$ is the depreciation rate of human capital while $A_S > 0$ and $a_S > 0$ and $b_S > 0$ are other parameters of the human capital accumulation with obvious interpretations.

All individuals own financial capital too. The stock of capital (or, wealth) owned by an (a, S, J) individual is $K_a^{S,J}$. The survival of an individual at age $a = a_0, \ldots, a_T$ in the next period is an uncertain event with probability $s_a \in [0,1]$. Death is a certain event at age $a_T = 85$. The capital stock $K_a^{S,J}$ is bequeathed to the offspring, if the individual is deceased at age a. Otherwise, the amount of bequest is zero. The amount of inherited bequest is denoted by B_a^J. Following Lee and Seshadri (2018), we assume that all individuals at age a_0 perfectly anticipate the bequest to be inherited in the future.

All individuals make a leisure-consumption choice. The instantaneous utility from consumption C and leisure L at age a is

$$U(C, L) = \mu_a \ln C + (1 - \mu_a)\frac{(L)^{1-\varphi}}{1 - \varphi}$$

where $\mu_a \in (0,1)$ determines the relative utility weight of consumption against leisure, depending on age. The parameter $\varphi \geq 0$ determines the elasticity of labor supply. When we empirically calculate the value of C, we will sum the household level expenditure on health, housing, food (away and at home), transportation, and education. Therefore, consumption can be interpreted as a composite good in a multi-sector economy. This multi-sector interpretation of our model will play an important role when we discuss innovation. Given the return on physical capital r, the intertemporal budget constraint is

$$K_{a+1}^{S,J} \leq (1 + (1 - \tau^K)r)K_a^{S,J} + B_a^J + (1 - \tau^L)W_a^{S,J} + \Pi_a^J - C_a^{S,J} \tag{2}$$

where τ^K and τ^L are the tax rates on capital and labor income, Π_a^J is the net profit income, and $W_a^{S,J}$ is the wage income of an (a, S, J) individual. If $a \leq a_R$, then the wage income of an (a, S, J) individual is

$$W_a^{S,J} = R_a^S H_a^{S,J}\left(1 - I_a^{S,J} - L_a^{S,J}\right) \text{ for } a_0 \leq a \leq a_R. \tag{3}$$

where R_a^S is the rental rate on human capital. Since $I_a^{S,J}$ is the time invested in human capital accumulation, and $L_a^{S,J}$ is the leisure time, the labor supply by an (a, S, J) individual corresponds to $1 - I_a^{S,J} - L_a^{S,J}$. Retirement at age $a_R = 65$ is mandatory and $P^{S,J}$ is the pension payment. Thus, when the individual is retired, the labor income is equal to the pension payment:

$$W_a^{S,J} = P^{S,J} \text{ for } a_R < a \leq a_T. \tag{4}$$

Note that the cost of education enters into the budget through consumption because consumption includes expenditure on education. Under these conditions, the individual solves the stochastic recursive problem below

$$V_a(H_a^{S,J}, K_a^{S,J}) = max\, U(C_a^{S,J}, L_a^{S,J}) + s_a \delta V_{a+1}(H_{a+1}^{S,J}, K_{a+1}^{S,J}) + (1 - s_a)\eta_a(K_{a+1}^{S,J})$$

subject to Eq (1) and (2) where $\delta > 0$ is the time preference, and $\eta_a(\cdot)$ is the utility from bequeathing at age a as in De Nardi and Yang (2016).

2.1. Optimality conditions

The conditions of optimality can be categorized according to whether the individual is employed or retired. Recall that $a = a_0, \dots, a_R$ if the individual is working, and $a = a_{R+1}, \dots, a_T$ if the individual is retired. Assume that survival before 65 years of age is a certain event, which means that $s_a = 1$ if $a_0 \leq a \leq a_R$. Thus, the first order conditions of this problem with respect to

$$\left(C_a^{S,J}, L_a^{S,J}, I_a^{S,J}, H_{a+1}^{S,J}, K_{a+1}^{S,J}\right)$$

at $a = a_0, \dots, a_R$ are the following:

$$\delta^a \frac{\mu_a}{C_a^{S,J}} - \lambda_a = 0$$

$$\delta^a(1 - \mu_a)\left(L_a^{S,J}\right)^{-\varphi} - \lambda_a(1 - \tau^L)R_a^S H_a^{S,J} = 0$$

$$\lambda_a R_a^S H_a^{S,J} + \zeta_a a_S A_S \left(I_a^{S,J}\right)^{a_S - 1}\left(H_a^{S,J}\right)^{b_S} = 0$$

$$\lambda_{a+1} R_a^S\left(1 - I_{a+1}^{S,J} - L_{a+1}^{S,J}\right) + \zeta_{a+1}\left(b_S A_S \left(I_{a+1}^{S,J}\right)^{a_S}\left(H_{a+1}^{S,J}\right)^{b_S - 1} + (1 - \sigma^S)\right) - \zeta_a = 0$$

$$-\lambda_a + \lambda_{a+1}(1 + (1 - \tau^K)r) = 0.$$

The tuple (λ_a, ζ_a) denotes the Lagrange multipliers for the dynamic budget constraint, and the law of motion for human capital accumulation, respectively. After eliminating these Lagrange multipliers by the method of substitution, the first order conditions reduce to

$$\frac{C_{a+1}^{S,J}}{C_a^{S,J}} - (1 + (1 - \tau^K)r)\delta \frac{\mu_{a+1}}{\mu_a} = 0 \tag{5}$$

$$\left(\frac{L_{a+1}^{S,J}}{L_a^{S,J}}\right)^{\varphi} - R_a^S H_a^{S,J}(1 + (1 - \tau^K)r)\delta \frac{1 - \mu_{a+1}}{1 - \mu_a} = 0 \tag{6}$$

$$(a_S A^S)\left(1 - I_{a+1}^{S,J} - L_{a+1}^{S,J}\right) + \left(\frac{b_S A_S \left(I_{a+1}^{S,J}\right)^{a_S} \left(H_{a+1}^{S,J}\right)^{b_S - 1} + 1 - \sigma^S}{\left(I_{a+1}^{S,J}\right)^{a_S - 1} \left(H_{a+1}^{S,J}\right)^{b_S - 1}}\right) \tag{7}$$

$$= (1 + (1 - \tau^K)r)\frac{R_a^S}{R_{a+1}^S}\left(I_a^{S,J}\right)^{1 - a_S}\left(H_a^{S,J}\right)^{1 - b_S}.$$

where $H_{a_0}^S$ and $K_{a_0}^S$ are given by assumption, and $I_{a_R}^S = 0$ due to optimality.

Now let us analyze optimality conditions for a retired individual. If $a = a_{R+1}, \dots, a_T$, which means that the individual is retired, then survival is not a certain event anymore. Upon death, the stock of capital is inherited by the offspring. Let the utility from bequeathing K to the offspring be

$$\eta_a(K) = (\phi_0 + a \times \phi_1)\frac{K^{1-\phi_2}}{1 - \phi_2}.$$

Moreover, upon retirement, all available time is spent on leisure, and no resource is spent on human capital accumulation. Hence, the first order optimality condition is simply

$$\delta^a \frac{\mu_a}{C_a^{S,J}} - s_a \delta^{a+1} \frac{\mu_{a+1}}{C_{a+1}^{S,J}} - (1 - s_a)(\phi_0 + a \times \phi_1)\left(K_{a+1}^{S,J}\right)^{-\phi_2} = 0. \tag{8}$$

As is well-know, the empirical evidence strongly suggests clear hump-shaped consumption and working hours patterns. To capture these observed patterns, we impose a time-varying flexible functional form on μ_a, the relative utility weight of consumption and leisure. To be specific, assume

$$\mu_a = \frac{m_1 + e^{-a \times m_0}}{1 + 2e^{-a \times m_0}} \tag{9}$$

where (m_0, m_1) is a fixed parameter tuple.

2.2. College Choice

The college choice is made at age $a = 18$. An 18 years old individual finds going to college optimal if the net sum of discounted wage income difference between college education and no college education ($S = 1$ or $S = 0$) is positive. To be specific, define

$$W^{S,J} = \sum_{a=a_0}^{65} (1 - \tau^L)\delta^a W_a^{S,J}$$

as the sum of net discounted wage income of an individual with schooling choice S from a J type family. The net income difference due to college education is

$$\Delta^J(H^J) = W^{1,J} - W^{0,J} - tuition - cost^J \tag{10}$$

where $cost^J$ includes psychic costs (of course, expressed in monetary terms) and all pecuniary costs that exceed the average tuition fee denoted by $tuition$. The parameter $cost^J$ depends on J to capture the fact that in real life parental income strongly affects how much a parent can afford to spend on the college education of his/her children. Note that the net income difference due to college education is a function of initial ability, H^J. So the formal optimality condition for schooling is

$$S = \begin{cases} 1 \text{ if } \Delta^{S,J}(H^J) > 0 \\ 0 \text{ if } \Delta^{S,J}(H^J) \leq 0. \end{cases}$$

The individual perfectly observes her ability, H^J, which is a random variable to any external observer. This completes our discussion of formulating the life-cycle model. The next subject is technology and innovation based on profit maximization.

3. Technology and innovation

Now we will discuss economic growth by incorporating a Schumpeterian model of innovation and technology into our analysis. In this model the economic growth is driven by technical change created by research and development (R&D). We assume that the firms invest in R&D to raise the probability of obtaining a superior technology and reducing marginal cost. Production of a firm with a lower marginal cost allows limit pricing, thereby discouraging competitors from entry. This would induce monopolization which constitutes the primary incentive of R&D investments by the profit maximizing firms. So the end result would be a constant pursuit of monopolization via technical change creating economic growth.

How is this classic Schumpeterian scenario related to redistributive policies? The link is the accumulation of human capital that positively affects monopoly profits, which spur R&D and innovation. Therefore, the redistributive policies would increase economic growth if those policies could achieve to incentivize higher levels of human capital accumulation. The validity of this scenario is examined when we study our numerical policy experiments. But now we first formally introduce the model.

3.1. A Schumpeterian model

The economic analysis of technology and innovation requires a multiple-good economy. So assume that the single consumption good C in the instantaneous utility function is a composite commodity as an aggregation of multiple differentiated goods

$$C = \left(\frac{1}{N} \sum_{i=1}^{N} (C_i)^{1/m} \right)^{m} \tag{11}$$

where C_i is the consumption of good i. The exogenous parameter $m > 0$ determines the elasticity of substitution between N number of commodities. Each good i is produced by firms that compete in prices a la Bertrand. Therefore, if all firms have the same technology, then the profits are zero assuming constant returns to scale. If, however, a firm obtains a technological advantage, then this firm would use limit pricing to drive its competitors out of the market, and earn a monopoly profit. This typical setup that describes the pricing-R&D interaction can be built on a representative firm under the appropriate symmetry conditions.

For the representative firm, the probability of successful innovation is $p(x)$ where $x \geq 0$ is the level of investment in R&D. If innovation is successful, then write $\pi > 0$ for the profit. Otherwise, the profit is zero. Thus, the expected level of profit from investing x in R&D is

$$p(x)\pi - x.$$

The corresponding first order condition is

$$p'(x)\pi = 1. \tag{12}$$

Given that the representative firm with a successful innovation produces Y amount of output, one can show that the level of profit is

$$\pi = m \times Y. \tag{13}$$

Recall that m is an exogenous preference parameter in Eq (11) but m in Eq (13) appears as the price-markup, or the market power of the technological leader in the market. The production technology is

$$Y = F(K, AH)$$

which exhibits constant returns to scale in K and AH. Here K is the level of physical capital,

$$H = \left(\xi H_0^{\beta} + (1-\xi)H_1^{\beta}\right)^{1/\beta}$$

is the CES composite level of human capital, and

$$H_S = \sum\nolimits_J \sum\nolimits_a H_a^{S,J}\left(1 - I_a^{S,J} - L_a^{S,J}\right) \tag{14}$$

is total supply of the human capital with education $S = 0{,}1$. The variable A is the efficiency of composite human capital H. Let $g > 0$ be a given constant. The current level of A increases to

$$(1+g)A$$

if innovation is successful, and does not change otherwise. Observe that the expected growth rate of technology is

$$p(x)g.$$

To close the model, let us assume

$$p(x) = 1 - e^{-r\frac{x}{y}} \tag{15}$$

where $y = Y/H$ is the output per human capital and $r > 0$ is a fixed parameter. The probability of success in R&D depends on x/y manifesting the idea that innovation becomes harder with each successful step forward in technological development. So define x/y as the research intensity. In this sense, the probability of success in R&D is determined by the research intensity, x/y.

Now the optimality condition with respect to investment in R&D in Eq (12) can be expressed as

$$r \times m \times H \times e^{-r\frac{x}{y}} = 1 \tag{16}$$

due to Eq (13) and (15).

This completes the theoretical model. Before discussing our empirical strategy, now we explain our data and data sources.

4. Data

Our major data source is the Panel Study of Income Dynamics (PSID) survey. We consider "head of household" in the PSID dataset as the "individual" in our model. The family background data J is constructed as follows. We first gather all child-parent couples. If the child or the parent has never been the head of household, then this couple is discarded. Then we calculate the average deflated income of each parent in the remaining group. We use the IMF's price deflator for this transformation. Then we rank parents according their level of income and divide them into three groups with equal sizes. This process gives us 2670 child-parent couples and the corresponding parental income levels: high, middle, and low income. Each child is an "individual" when s/he becomes "head of household".

The schooling data S is constructed by setting $S = 1$ for individuals with four years of college education or more, and $S = 0$ for less than four years of college. Let the set of all (a, S, J) individuals at time $y \in Y = \{1999, 2001, \ldots, 2015, 2017\}$ in our dataset be denoted by $D(a, S, J, y)$.

Let X be the set of variables for which we have data. The variables in X provided by PSID survey include working hours (l), labor income (w), and capital (k). The consumption variable (c) is computed by adding up food away, food home, housing, education, child care, health, and transportation expenditures. The original annual working hours data is divided by 16×365 to construct (l) data. This means an individual is assumed to have 16 hours of free time per day, and total available free time per annum is normalized to 1. Labor income (w) and capital (k), which are originally expressed in current prices, are transformed into constant prices using the IMF's price deflator. Hence, if $x = c, l, w, k$, then we have a vector of observations

$$\left(c_{a,i}^{S,J}, l_{a,i}^{S,J}, w_{a,i}^{S,J}, k_{a,i}^{S,J}\right)$$

for each $i \in D(a, S, J, y)$.

Number of young individuals who choose to go to college at each year is calculated as follows. First, all individuals with a college degree in the PSID data is collected. Then we calculate the year when these college graduates were 18 years old. This gives us how many individuals choose to go to college in year $y \in Y = \{1999, 2001, \dots, 2015, 2017\}$, denoted by n_y^1. The same method gives us n_y^0, the number of 18 years old individuals in year y who will not have a college degree. The annual tuition cost data is provided by the Bureau of Labor Statistics.

To estimate the model, we also invoke some macro data and calibration values. The real rental rate of capital (net of depreciation) is assumed to be $r = 0.03$. Taxes levied on labor and capital income are $\tau^L = 0.25$ and $\tau^K = 0.15$, respectively. To be consistent with the long term growth performance of the US economy according to the Penn World Table (PWT) data, the growth of the rental rate of human capital is set to 2%, which means

$$\frac{R_{a+1}^S}{R_a^S} = 1.02. \tag{17}$$

The pension $P^{S,J}$ is calculated as 40% of the average gross wage income of the individual. To make the model consistent with economy wide observations, profit income is assumed to be 1/3 of labor income.

5. Estimation method

The life-cycle of an individual consists of three basic periods, which involve schooling choice ($age < a_0$), employment ($a_0 \leq age \leq a_R$), and retirement ($a_R < age \leq a_T$). The schooling choice is estimated by maximum likelihood. The employment and the retirement periods are estimated by weighted nonlinear least squares. The technology parameters are calibrated by using the estimation of the life-cycle parameters.

5.1. Employment period

To estimate the parameters related to the employment period, we use the non-linear least squares technique following Heckman et. al. (1998). More specifically, we find the parameters that minimize the weighted sum of squared differences between optimal behavior according to Eq (1)-(7) and observed behavior according to the PSID survey in logarithms. The weights are inversely related to the empirical standard deviation of each variable $x = c, l, w, k$, denoted by $\omega_{a,x}^{S,J}$ for (a, S, J) type individuals. Formally, the sum of squared errors

$$\sum\nolimits_{x=c,l,w,k} \sum\nolimits_{a,S,J,y} \sum\nolimits_{i \in D(a,S,J,y)} \left(\frac{\ln\left(x_{a,i}^{S,J}\right) - \ln\left(x_a^{S,J}\right)}{\omega_{a,x}^{S,J}} \right)^2 \tag{18}$$

is minimized by choosing the parameters

$$\{(\sigma, \varphi, \delta, m_0, m_1), (A_S, a_S, b_S)_{S=01}\}$$

and optimal individual behavior

$$\left(c_a^{S,J}, l_a^{S,J}, i_a^{S,J}, h_a^{S,J}, k_a^{S,J}\right)$$

subject to the optimality conditions in Eq (1)-(7) for all $S = 0,1$ and $J = L, M, H$ and $a = a_0, \dots, a_R$. For future reference, let $\overline{H}^{S,J}$ denote the estimated initial human capital of an individual with education S, and family background J.

5.2. Retirement period

Next, we move to the retirement period when $a = a_{R+1}, \dots, a_T$, and minimize

$$\sum_y \left(\sum_{a,S,J} \sum_{i \in D(a,S,J,y)} \frac{\ln\left(k_{a,i}^{S,J}\right) - \ln\left(k_a^{S,J}\right)}{\omega_{a,k}^{S,J}}\right)^2 \tag{19}$$

subject to the optimality conditions in Eq (1)-(8) and the solution to the estimation problem in Eq (18) by choosing the parameters of utility from bequest (φ_0, φ_1) and optimal individual behavior $\left(c_a^{S,J}, k_a^{S,J}\right)$ for all $S = 0,1$ and $J = L, M, H$ and $a = a_{R+1}, \ldots, a_T$.

Note that we take the sample mean of our $\ln k$ data over all types of individuals so we do not distinguish between different family backgrounds or education levels at the retirement stage. This practice is a consequence of the fact that the number of observations for each type of individual dramatically decreases as $a \to a_T$. However, ignoring the heterogeneity among individuals in the data is not a serious problem at the retirement stage because the estimated parameters (φ_0, φ_1) at this stage are identical for everyone. In fact no preference parameter in the present paper is differentiated according to schooling choice or family background.

5.3. Schooling choice

We finally move to the schooling choice which means $a = 18$. At this final stage of estimation, we maximize the probability of observing the actual college education choices in the PSID data by determining the parameters of uncertainty in ability $\left(a_0^J, a_1^J\right)$, and the parameters of college education $(\rho^J, cost^J)$ depending on family background $J = L, M, H$.

Recall that H^J denotes the initial ability of an individual from a J type family prior to the schooling choice. Let $H^{J,*}$ denote the threshold level of initial ability to be indifferent between college and no college for an individual from a J type family. Thus, by definition, $H^{J,*}$ solves $\Delta^J(H^{J,*}) = 0$ (see Eq (10)).

Let $G^J(H^J)$ denote the cdf of the random initial ability H^J. So the probability that an arbitrary individual from a J family background would choose to go to college is

$$Pr^J = \int_{H^{J,*}}^{\infty} dG^J(H).$$

This probability lies in the core of maximum likelihood estimation, and it depends on the threshold level $H^{J,*}$. As a computational prerequisite, the threshold initial ability $H^{J,*}$ should be solved as a function of schooling parameters $(cost^J, \rho^J)$ prior to the maximum likelihood estimation.

To this end, we use the Chebyshev polynomial approximation method at two different levels. First, the theoretical labor supply and capital stock at age 65 at the estimated parameter values are computed at 20 different points of initial ability for each (S, J) type individual. Then we use the 20th degree Chebyshev polynomial for the approximation which gives us labor supply and capital at age 65 as a function of initial ability. This step is computationally a time-consuming part of the estimation process. Then, given the labor supply and capital stock at age 65 as (Chebyshev polynomial) functions of initial ability, all other optimal decisions are solved in a backwards fashion, giving us the income levels over the life-cycle, again, depending on initial ability. So the net income difference due college education, Δ^J, can be computed at different initial ability levels for any given $(cost^J, \rho^J)$ tuple. Thus, the threshold ability $H^{J,*}$ solving the indifference condition $\Delta^J = 0$ can be computed for any level of college parameters $(cost^J, \rho^J)$. We approximate this relation between $H^{J,*}$ and $(cost^J, \rho^J)$, again using a Chebyshev polynomial (2nd order 10th degree). This second step finally allows us to compute the probability of going to college Pr^J as a function of college parameters, $(cost^J, \rho^J)$. Recall that Pr^J also depends on (a_0^J, a_1^J), the ability parameters, by definition.

Now we can compute the log-likelihood of that n_y^1 number of people would choose $S = 1$ and n_y^0 number of people would choose $S = 0$ in all periods $y \in Y$. The result is:

$$LP\left(cost^J, \rho^J, a_0^J, a_1^J\right) = \sum\nolimits_{y \in Y} \left(n_y^1 \times ln\, Pr^J + n_y^0 \times ln(1 - Pr^J)\right).$$

Given the solutions to the estimation problems in Eq (18)-(19), the standard maximum likelihood estimation is to solve

$$\max LP\left(cost^J, \rho^J, a_0^J, a_1^J\right)$$

subject to

$$\overline{H}^{1,J} = \int_{H^{J,*}}^{\infty} H \times (1+\rho^J) \times dG^J(H) \text{ and } \overline{H}^{0,J} = \int_{0}^{H^{J,*}} H \times dG^J(H)$$

by choosing the education and ability parameters $\left(cost^J, \rho^J, a_0^J, a_1^J\right)$ for all $J = L, M, H$. As is discussed earlier, $\overline{H}^{S,J}$ is the estimated initial human capital of an individual with a schooling choice S, and a J type family background. This quantity is already available as a numerical value as it is estimated in the employment stage.

An important consistency condition is satisfied due to the constraint of this maximum likelihood estimation. In particular, the distributions of pre-employment initial ability levels according to the maximum likelihood estimation are perfectly consistent with the conditional means of post-college-choice initial human capital levels according to the nonlinear least square estimations. In other words, the estimated parameters of the schooling period and the employment period are consistent with each other according to the life-cycle model of the present essay

6. Estimation results

In this section we present our estimation results, starting with the parameters depending on the parent's income. These parental background parameters include the mean and variance of initial ability and the cost and return of college education. The initial wealth owned by young adults also depends on whether the parents are low, medium, or high-income earners. Hence, the existence of unequal opportunities, or lack thereof, among children is determined by these parameters.

According to Table 1, the average pre-college ability of a child increases as the parent's income level increases. The rate of return and the cost of college education also increase with parental income. This result is unsurprising and it means that young individuals from higher-income families have higher abilities prior to college, and then, go to better colleges, and spend more

Table 1. Estimated parameters that depend on parents' income.

Family background	Rate of return to college education	Cost of college	Average pre-college ability	SD of ability	Initial wealth $S=0$	Initial wealth $S=1$
High Income	0.16*** (0.001)	1.84*** (0.027)	3.11*** (0.023)	0.32*** (0.02)	1.47*** (0.48)	2.35*** (0.42)
Medium Income	0.13*** (0.0002)	1.05*** (0.005)	2.62*** (0.0085)	0.20*** (0.0013)	1.36* (0.79)	2.00*** (0.64)
Low Income	0.12*** (0.00013)	0.57*** (0.045)	2.33*** (0.014)	0.19*** (0.0066)	1.18*** (0.50)	1.99 (2.14)

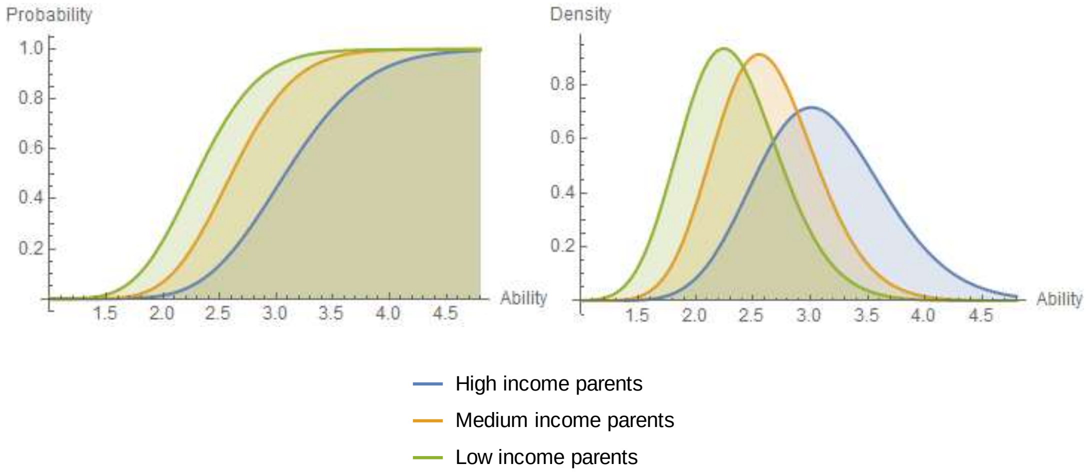
Notes. Standard deviations are in parentheses. *: Significance at 10%, **: Significance at 5%, ***: Significance at 1%.

resources on college education than other individuals. The cumulative and density distributions of initial abilities according to the family background are given in Figure 1.a. and 1.b., respectively.

Of course, no child could be held responsible for the economic status of their parents. Nevertheless, according to our estimation results, children from higher income families go to superior colleges so that the children from lower income families lag behind in terms of income all through their adult lives. Consequently, these results suggest inequality of opportunity among young adults with significant effects over the life-cycle.

Figure 1.a. CDF of initial abilities among children. (Left)

Figure 1.b. PDF of initial abilities among children. (Right)



Moreover, the initial wealth levels of young adults are also positively related to the income level of their parents. Therefore, there is another layer of inequality of opportunity related to wealth, akin to education. The wealth gap among young adults is an overlooked issue in the literature of intergenerational analysis of unequal opportunities. Having said that, one may argue that it is not clear whether our results conclusively demonstrate the existence of unequal opportunities. Suppose that the initial ability gap between children as can be seen in Table 1 is solely due to heritable genetic factors such as IQ. This would explain why rich kids go to better colleges and invest more in education: they are smarter. Moreover, the fact that the rich kids go to better colleges would not violate the basic principles of equality of opportunity assuming that the IQ level is a personal responsibility. We will take this scenario into account in our simulations.

Nevertheless, the IQ debate reminiscent of the classic nurture vs. nature conundrum is not directly the subject of our analysis.[4] Instead, our objective is to quantify the optimal responses

[4] It is also noteworthy that the IQ objection is not very strong. First of all, it does not apply to the financial aspect of the inequality of opportunity, pointed out by our estimation results. More specifically, it is not clear how higher IQ could justify possessing higher levels of initial wealth, which is clearly linked to parental income. Second, neither IQ is fully determined by genetic factors nor initial ability is completely shaped by IQ. Therefore, IQ as a heritable genetic factor is not enough to fully explain the ability gap between children from different economic backgrounds. So it stands to reason that inequality among parents has at least some role to explain the pre-college ability gap between children.

Table 2. Estimated preference parameters						
Elasticity parameter	Time preference	Weight parameters		Bequest parameters		
φ	δ	m_0	m_1	η_0	η_1	η_2
2.69*** (0.23)	0.996*** (0.0023)	0.111*** (0.03)	0.0074 (0.01)	-1.51*** (0.065)	0.16*** (0.0075)	0.74*** (0.093)

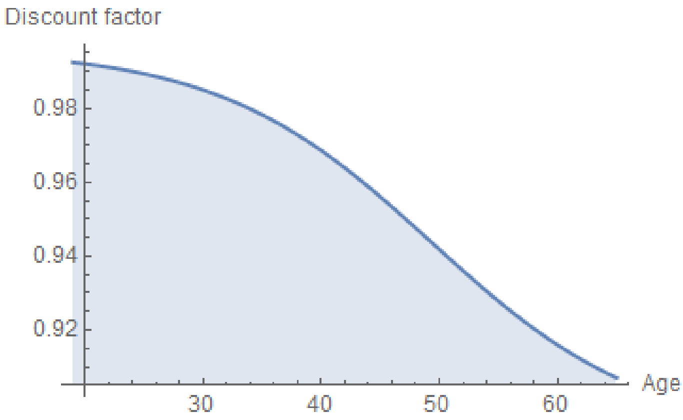
of individuals to certain policies designed to level the playing field. Hence, in the present context, the preference parameters of individuals are more crucial than the nature vs. nurture conundrum. Table 2 presents the estimates of these preference parameters. For example, we find $\delta = 0.996$ for the time preference which is directly linked to the discount factor. However, the standard value for the discount factor in the literature is 0.96, which is significantly lower than our estimation. That is because, the proper discount factor is

$$\delta \frac{\mu_{a+1}}{\mu_a}$$

which gives us the present value of $1 in the next year. This claim can be easily verified by inspecting Eq (5). The intuition is that the proper discount factor takes the impact of aging into account. As can be seen in Eq (9), by definition, the impact of aging μ_a is determined by the tuple (m_0, m_1), which is estimated to be (0.111,0.074). The estimated age-dependent discount factor $\delta \times (\mu_{a+1}/\mu_a)$ is plotted in Figure 1. It turns out to be very close to 0.96 on average, 0.957 to be specific.

Next we discuss the elasticity parameter φ, which is pivotal to the elasticity of labor supply, and crucial for our purposes. The impact of taxation on labor supply and human capital accumulation incentives is determined by the elasticity of labor supply. A low elasticity of labor supply is the conventional wisdom in the literature although this view has been recently challenged. We estimate $\varphi = 2.69$, suggesting inelastic labor supply, and supporting the conventional wisdom.

Figure 1. The estimate of the discount factor



Notes. Calculated as $\delta \times (\mu_{a+1}/\mu_a)$ at the parameter estimates in Table 2.

Nevertheless, the studies that estimate the elasticity of labor supply typically do not involve human capital accumulation. Human capital accumulation in our model – similar to Keane and Wasi (2016) - means that the labor supply elasticity is age-dependent. Thus, to compare our result to the literature, the Frisch elasticity of labor supply is plotted in Figure 2. In particular we compute

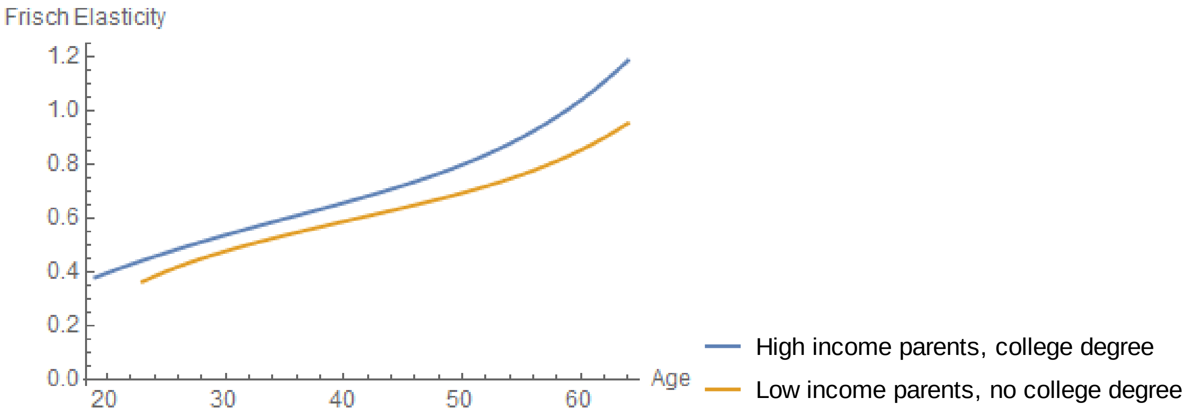
$$\frac{d\, ln\left(1 - I_{a+1}^{S,J} - L_{a+1}^{S,J}\right)}{d\, ln(1 - \tau^L)}$$

under the assumption that the marginal utility of consumption is unchanged.

The Frisch elasticities of labor supply presented in Figure 2 are similar to the figures obtained by Keane and Wasi (2016). According to their estimates, the Frisch elasticity of labor supply increases over the life-cycle, starting approximately from 0.5 and exceeds 1 when the individual is around 60 years old. Moreover, they also find that elasticity decreases with education. Our elasticity estimates also exhibit the same features as can be seen in Figure 2. The fact that our model incorporates human capital accumulation during the employment period is the primary reason why our results are similar to those of Keane and Wasi (2016).

The estimated parameters of human capital accumulation are presented in Table 3. The results show that all these parameters are higher if an individual has a college education. College

Figure 2. Frisch elasticities of labor supply over the life-cycle.



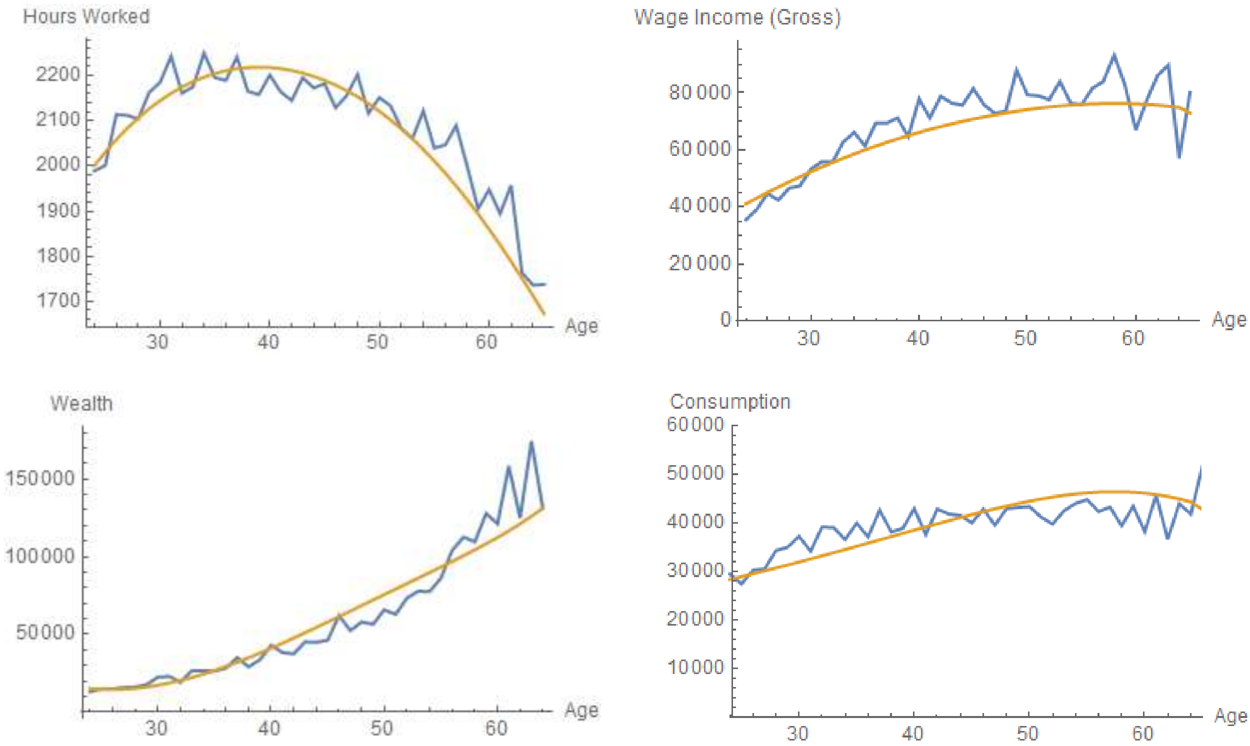
education, of course, increases human capital after graduation at the age of 23. But it also enhances the impact of training over the life cycle. In other words, college education of young people enables them to accumulate more human capital until they are 65.

Table 3. Estimated Parameters of human capital accumulation technology.

No college			College			Depreciation rate
α_0	β_0	A_0	α_1	β_1	A_1	σ
0.59*** (0.24)	0.87*** (0.25)	0.044** (0.02)	0.77*** (0.22)	1.07*** (0.28)	0.052*** (0.021)	0.007 (0.02)

This explains why the wage gap between employees with and without college degree is quite large despite the fact that the return to education is around 15%. The college education is not a single boost to the human capital of an individual. Instead, individuals with a college degree can constantly improve themselves until they retire. That, of course, contributes to intergenerational

Figure 3. Data vs. Model over the employment period.

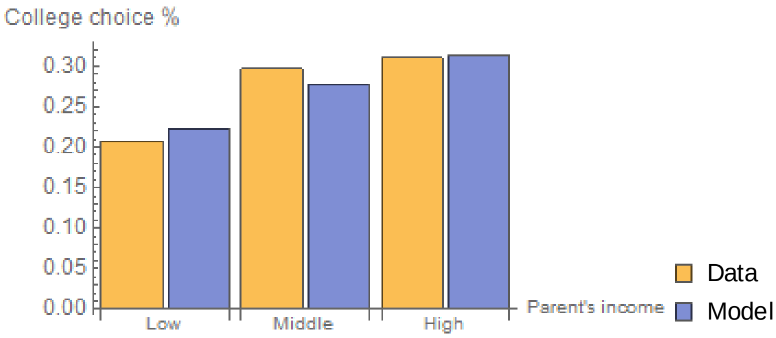


Notes. All variables are population weighted averages. All variables (except hours worked) are in 2017 dollars.

inequalities. That is also the reason why human capital accumulation via on-the-job-training is crucial in our model.

To visually inspect the fit of the model to the data, we plot the model's estimated predictions against the actual data in Figure 3. In terms of capturing the life-cycle trends, the model's fit is quite accurate. Nevertheless, the model is inherently smooth and fails to capture non-smooth fluctuations in wage income, wealth, consumption, and working hours. That is because, the discount factor is the only age dependent exogenous of the model, and it is very smooth as can be seen in Figure 1. This could had been a troubling shortcoming if our objective had been capturing the cyclical nature of these variables. Yet our primary objective is to see the interaction between human capital accumulation and redistributive policies to combat unequal opportunities as discussed above.

Figure 4. Ratios of individuals who choose college education according to different family backgrounds.



Net we discuss the college choices. In Figure 4, the average ratio of individuals who choose to go to college are presented according to parental backgrounds. First of all, the fit of the model is still accurate as the maximum error of the model is less than 2%. The figures show that the ratio of individuals that choose to go to college vary between 20-30%. Moreover, there is very little difference in terms of college choice between the children of high and middle income parents. However, people from low income families significantly lag behind as only 20% of them choose to have a college education.

Finally we calibrate our Schumpeterian model. First of all, according to the BLS, the profit share in GDP in the US is approximately 1/6. This ratio gives the price-markup as

$$m = \frac{\pi}{Y} = \frac{1}{6}. \tag{20}$$

According to the OECD data, the R&D-to-GDP ratio in the US is

$$\frac{x}{Y} = 2.7\%. \tag{21}$$

Our estimations suggest that

$$H_0 = 32.21 \text{ and } H_1 = 13.04 \tag{22}$$

Table 4. Calibration values for technology related variables.

Variable	H_0	H_1	College/no-college labor share ratio	β	ξ
Value	32.21	13.04	1.035	0.306	0.46
Source	Author's estimate	Author's estimate	PSID	Heckman et. al. (1997)	Eq (22)(24)

which are the aggregate supplies of human capital by no-college and some college individuals, respectively, as defined in Eq (14). According to the PSID data, the total labor income shares of some college to no-college individuals is

$$\frac{\text{Total college labor income}}{\text{Total no} - \text{college labor income}} = 1.035. \tag{23}$$

Observe that Eq (23) gives us an empirical ratio. The same ratio (i.e. labor income shares of college and no-college individuals) should be theoretically equal to

$$\frac{\text{Total college labor income}}{\text{Total no} - \text{college labor income}} = \frac{H_1 \times MP_1}{H_0 \times MP_0} = \frac{1-\xi}{\xi} \times \left(\frac{H_1}{H_0}\right)^{\beta} \tag{24}$$

where MP is the marginal productivity. Finally, Heckman et. al. (1997, p. 26) estimate that $\beta = 0.306$ which implies that $\xi = 0.56$ due to Eq (22)(23)(24). So the calibrated values of the fixed parameters and other relevant variables are summarized in the table below.

Now the only variable without a numerical value is r. To find the numerical value of r, we can solve Eq (16) in r by taking into account the results in Table 8 and the aggregate data in Eq (21) and Eq (20). This means that we should solve $2.885re^{-0.467r} = 1$. There are two solutions. The first solution is $r = 4.78$ and is discarded because it implies an increase in aggregate human capital H reduces the optimal R&D density. The second solution is $r = 0.33$ and we continue our analysis with this value. This concludes the Schumpeterian model of innovation and its calibration. Now we can conduct counterfactual analysis and study the implications of certain policy experiments on wealth, human capital, and technology.

7. Policy experiments

Our results indicate that the children from high income families go to the best colleges by paying the highest costs while the children from middle and low income families go to inferior colleges with lower initial abilities. These results are consistent with the literature which emphasizes that the income inequality among adults creates unequal opportunities in education for children, perpetuating the income inequality in the future.

In this section, we conduct policy simulations that are designed to address this reciprocal cause and effect relationship between income inequality and unequal opportunities. As the root cause of this vicious circle seems to be the distribution of income among parents, we restrict our attention to redistributive policies. Our objective is to see whether unequal opportunities prevent accumulation of wealth and human capital that are crucial for the incentives of investing in innovation by profit maximizing firms. This chain of links between inequality, economic policies, accumulation, and innovation is our major focus.

Of course, there are other relevant policies that are not directly redistributive, e.g. reducing the cost of education, subsidizing entrepreneurship, etc. However, these policy alternatives are out of our scope. Now let us explain how we study the redistributive policy experiments and conduct the numerical simulations.

Simulation guidelines

To run the policy experiments, we use the estimated parameter values presented in Section 5 and 6. First we randomly draw 1000 observations from the individuals' ability distributions for each parental background: low, middle, high income. Then we calculate the optimal behavior of each individual under a given policy experiment. The policy experiment induces a new optimizing behavior of individuals over their life-cycles, giving us a new income distribution among adults (3000 people in total). To calculate the life-cycle behavior of the next generation, the social status of children should be determined. This brings us to the topic of social status transmission from one generation to the next.

In the simulations, we consider two polar cases for intergenerational social status transmission: "*Nature*" and "*Nurture*". In the case of the *Nature* scenario; low, middle, and high income groups have equal sizes, no matter what policy is in place. Therefore, the ratio of children from each ability group is constant with respect to the economic policies. This scenario can be interpreted as ability being determined by non-economic or genetic factors such as IQ.

The opposite end of the spectrum is the *Nurture* scenario, which means that low, middle, and high income groups are delineated according to income threshold levels. According to the PSID data, measured in 2017 dollars, any individual whose annual wage income is less than $23K is at the bottom 33.3% while wage income higher than $43K corresponds to the top 33.3%. In the *Nurture* scenario, we use these threshold levels to determine the family background of children. For example, an economic policy could increase the number of adults with annual wage more than $23K. Under the *Nurture* scenario, this would mean more children are endowed with the ability parameters of middle and high income (i.e. more than $23K per annum) social status. So the *Nurture* scenario reflects the idea it is the parental income that determines the initial abilities of the children while leaving no room for non-economic factors such as genes to play a role.

The initial wealth of a child from a J type family is determined by the average bequests of J type families. This keeps the number of individual types bounded by ensuring that there are always three groups of family backgrounds. So the intergenerational transmission of initial parameters (i.e. ability and wealth) is specified.

After social status transmission is completed under these specifications, the simulations are re-run for the next generation. This iterative process continues until convergence in income and

Table 5: Percentage changes in aggregate outcomes caused by Policy 1.			
Transmission of social status	Wealth	Human capital	Growth
Nurture	-0.15%	0.1%	0%*
Nature	-0.1%	0.07%	0%*
Notes. The percentage changes relative to the status-quo. Wealth is aggregated by ordinary summation. Human capital is aggregated according to Eq. (13)). Growth is the growth of GDP per capita, determined by the R&D investments of the firms. *: Less than 0.01% but positive.			

wealth distribution occurs. As we shall see, the impacts of the *Nature* vs. *Nurture* distinction are as expected. However, the difference is so small that they make no qualitative effect in terms of long-term growth in any policy experiment. The first policy experiment is our benchmark case for equality of opportunity.

Policy 1: Universal lump-sum taxation and transfers to adults raised in low income families. This policy is our benchmark for levelling the playing field. According to this policy, the transfers and taxes start at the age 23 for college graduates and 19 for others. The individuals whose parents are poor receive $1000 per annum if they have no college education. Its discounted sum is approximately equivalent to a single lump-sum $25.000 transfer at the age of 19. The amount of transfer to an individual with a college degree and a low income family background is $1,036 per annum.[5] Individuals from middle and high income families do not get transfer payments. To finance these transfers, all working individuals with no college education pay $300 per annum. All working individuals with some college education pay $311 per annum. These taxes and transfers are effective until retirement. The budget government budget is balanced.

[5] The differences in taxes and transfers according to education compensate for the fact that college graduates enter the labor market 4 years later.

Table 6: Percentage changes in individual behavior caused by Policy 1.						
Parent's income	Low		Medium		High	
Education	College	No-college	College	No-college	College	No-college
Size	-0.52%	0.27%	0.66%	-0.32%	-0.11%	0.05%
Human capital	0.82%	0.95%	-0.31%	-0.36%	-0.25%	-0.30%
Wealth	-3%	-5.5%	1.3%	2%	1.12%	1.6%
Bequest	-2.8%	-1.8%	1%	0.7%	0.56%	0.8%

Notes. The percentage changes relative to the status-quo. Size is the ratio of individuals with the schooling, choice $S = 0{,}1$ and the family background, $J = L, M, H$. Human capital, wealth, and bequest are at the expected values at the individual levels.

The aggregate impact of this policy on accumulation and economic growth can be seen in Table 5. So our benchmark policy has a small positive effect on the total human capital (between 0.07% and 0.1%) and a small negative effect on the total wealth accumulation (between -0.1% and -0.15%). The net effect of these two opposite forces on long-term economic growth is almost zero. Therefore, the growth rate of GDP per capita is practically still 2% according to our benchmark policy. Recall that 2% is the growth rate of GDP per capita under status-quo as discussed in Section 6. It is interesting to note how close the results are in both *Nurture* and *Nature* scenarios. This similarity in outcomes will be observed in other policy experiments too.

We only report the aggregate results in Table 5. Now let us see how this policy affects the individual behavior. As is shown in Table 6, the percentage changes in wealth and bequest on an individual basis, especially for individuals from low income families, is quite sizeable (i.e. -3% and -5,5%). To a lesser extent, this is also true for human capital accumulation (i.e. 0.82% and - 0.95%). Nevertheless, the most crucial aspect of these figures is that human capital accumulation of children from low and middle income move in opposite directions (for instance,

Table 7: Percentage changes in aggregate outcomes caused by Policy 2.			
Transmission of social status	Wealth	Human capital	Growth
Nurture	3.6%	0*%	0*%
Nature	3.5%	0*%	0*%
Notes. The percentage changes relative to the status-quo. Wealth is aggregated by ordinary summation. Human capital is aggregated according to Eq. (13)). Growth is the growth of GDP per capita, determined by the R&D investments of the firms. *: Less than 0.01% but positive.			

0.82% vs. -0.31% for college graduates). That is the reason why, we observe very small aggregate changes in Table 5 because the opposite individual effects neutralize each other.

The ethical justification of Policy 1 is based on the fact that this policy compensates for disadvantageous low income parental background, consistent with the basic principles of equality of opportunity. Nonetheless, this policy creates another ethical problem as it grants unconditional transfer payments even to people who are high income earners, provided that their parents are low-incomers. The second policy experiment is designed to solve this ethical problem.

Policy 2: Progressive transfers according to income and lump-sum taxation of everyone.

The second policy experiment stipulates everyone without a college degree to pay $175 per annum as a lump-sum tax. The amount of tax for college graduates is $182 per annum. Tax revenues are distributed to people from low income families in a progressive fashion. In particular, eligibility requires less than $32,000 wage income per annum. The transfer rate starts from 0% when the annual wage income is $32,000 and it reaches to 25% at $14,000 annual wage income.

The individuals' wage levels vary over the life-cycle. That is the reason why, on average, a college graduate from a low income family would be eligible for the transfer payments for 5 years whereas the transfer payments would continue for 20 years for individuals with no college

Table 8: Percentage changes in individual behavior caused by Policy 2.

Parent's income	Low		Medium		High	
Education	College	No-college	College	No-college	College	No-college
Size	-3.6%	1.9%	-0.41%	0.2%	4.15%	-2.08%
Human capital	0.16%	-0.02%	0.15 %	-0.18%	0.12%	0.15%
Wealth	-1.22%	27.7%	-0.36%	0.7%	-0.53%	2.90%
Bequest	-0.4%	18%	-0.36%	-0.5%	-0.28%	0.06%

education. Of course, these payment periods are endogenous outcomes determined by the optimal behavior of individuals given the rules of our policy experiment. The government budget is, again, balanced for this tax-transfer scheme.

At the aggregate level, the impact of this policy is very strong on capital accumulation, causing an increase around 3.5-3.6% in total wealth. Nonetheless the policy impact on human capital is extremely small: less than 0.001% but positive. So the average growth rate of GDP per capita is practically still 2% under this policy experiment.

To see why this is the case, consider the individual responses to the policy experiment reported in Table 8. The children from low and medium income families college enrollment drops in a significant way (i.e. -3.6% and -0.41%). Moreover, people without college degree also lower

Table 9: Percentage changes in aggregate outcomes caused by Policy 3.

Transmission of social status	Wealth	Human capital	Growth
Nurture	-0.89%	2.79%	0.16%
Nature	-0.8%	2.23 %	0.12%

Table 10: Percentage changes in individual behavior caused by Policy 2.

Parent's income	Low		Medium		High	
Education	College	No-college	College	No-college	College	No-college
Size	7,9%	-2.3%	5.8%	-2.2%	3.14%	-1.4%
Human capital	-0.05%	-0.12	0.05%	0%*	0.18%	0.14%
Wealth	-1.81%	0.6%	-0.76%	0%**	-1.6%	-0.70%
Bequest	-2.79%	-2.81%	-3.39%	-3.8%	-2.74%	-2.66%

Notes. *: Less than 0.01% but positive. **:More than -0.01% but negative.

their human capital accumulation if their background is either low or middle income (i.e. -0.02% and -0.18%).

Despite these negative figures, there is an increase in college enrollment by the children from high income families (4.15%). They also raise their human capital accumulation. So these opposite forces again neutralize each other making a negligible positive impact on innovation and growth.

Policy 3: Lump-sum transfer to everyone financed by sales taxes.

Our final policy simulation can be considered as a universal basic income experiment. All individuals receive unconditional $850 per annum as transfer payment (regardless of income or background). This transfer scheme is financed by an extra 3% tax on consumption.

Note that this final policy yields the highest rate of growth in all scenarios. The reason is that this particular universal basic income experiment induces the highest level of aggregate human capital. As can be seen in Table 10, the college enrollment rates for all children from all economic backgrounds substantially increase under the universal basic income policy. For instance, there is 3.14% increase in college enrollment for children from high income families while the same rate is 5,8% for children from middle income families. The rate of human capital accumulation is, however, almost unaffected (e.g. -0.05% and 0.05% for college graduates from low and middle income families, respectively).

Observe that Policy 3 does not directly compensate for early childhood disadvantages. However, we believe it still qualifies as a policy to combat the inequality of opportunity. That is because, the universal basic income has two properties: lowering income inequality and providing financial assistance regardless of parental background. Therefore, an individual from a low income family would be a net beneficiary of a guaranteed income policy. That is the reason why we maintain that the universal basic income can be used as a tool for enhancing equality of opportunity.

8. Conclusion

Inequality of opportunity could potentially hamper economic growth by wasting the most valuable economic resource – human intellect. If low income parents cannot provide the adequate education for their children due to lack of financial resources, this would impede human capital accumulation in the economy. Human capital is, however, a key factor that determines the incentives of profit-maximizing firms to invest in innovation, which is widely considered to be the engine of growth of GDP per capita.

In this study, we ask how redistributive policies that are intended to level the playing field among children from different socio-economic backgrounds would affect this interaction between innovation and inequality. To this end, we develop a dynamic model where initial abilities of children are determined by their parents' income levels. The initial ability influences individuals' optimal behavior over the life-cycle, including schooling and human capital accumulation. Given the aggregate human capital in the economy, firms invest in innovation to maximize their profits. This model is estimated using the longitudinal US data from 1999 to 2017. Then we conduct counterfactual analysis by simulating the model under three different hypothetical policies.

According to the numerical results, all policies induce positive effects on economic growth. The first two of these policies directly compensate for disadvantageous early childhood, and their effects are very small. The third policy is a universal basic income program financed by higher sales taxes. This policy creates a substantial impact on human capital accumulation, innovation, and economic growth.

The reason behind small effects for the first two policies is primarily what we call as "substitution effect" and it operates as follows. Compensating for early childhood disadvantages directly implies lower skill-premium, the wage gap between skilled and unskilled workers. Lower skill-premium, however, discourages young people from going to college and accumulating human capital. Of course, substitution effect is not the only impact caused by the policy experiments. Nevertheless, the results empirically demonstrate that the substitution effect can be strong enough to weaken but not strong enough to overwhelm the potentially positive effects of equality of opportunity policies. Taking the risk of being repetitive, in all our simulations, the impact of equality of opportunity policies on innovation and growth is small but positive.

References

Abbott, B., Gallipoli, G., Meghir, C., & Violante, G. L. (2019). Education policy and intergenerational transfers in equilibrium. *Journal of Political Economy*, *127*(6), 2569-2624.

Acemoglu, D., & Pischke, J. S. (2001). Changes in the wage structure, family income, and children's education. *European Economic Review*, *45*(4-6), 890-904.

Becker, G. S., & Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of labor economics*, *4*(3, Part 2), S1-S39.

Cagetti, M., & De Nardi, M. (2006). Entrepreneurship, frictions, and wealth. *Journal of political Economy*, *114*(5), 835-870.

Dabla-Norris, M. E., Kochhar, M. K., Suphaphiphat, M. N., Ricka, M. F., & Tsounta, E. (2015). *Causes and consequences of income inequality: A global perspective*. International Monetary Fund.

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

De Nardi, M., & Fella, G. (2017). Saving and wealth inequality. *Review of Economic Dynamics*, *26*, 280-300.

Fan, X., Seshadri, A., & Taber, C. (2017). Understanding Earnings, Labor Supply, and Retirement Decisions. *Michigan Retirement Research Center Research Paper*, (2017-367).

Galor, O. (2011). Inequality, human capital formation, and the process of development. In *Handbook of the Economics of Education* (Vol. 4, pp. 441-493). Elsevier.

Galor, O., & Tsiddon, D. (1997). The distribution of human capital and economic growth. *Journal of Economic Growth*, *2*(1), 93-124.

Heckman, J. J., Lochner, L., & Taber, C. (1998). Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents. *Review of economic dynamics*, *1*(1), 1-58.

Keane, M. P. (2016). Life-cycle labour supply with human capital: econometric and behavioural implications. *The Economic Journal*, *126*(592), 546-577.

Keane, M. P., & Roemer, J. E. (2009). Assessing policies to equalize opportunity using an equilibrium model of educational and occupational choices. *Journal of Public Economics*, *93*(7-8), 879-898.

Keane, M. P., & Wasi, N. (2016). Labour supply: the roles of human capital and the extensive margin. *The Economic Journal*, *126*(592), 578-617.

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

Lee, S. Y., & Seshadri, A. (2019). On the intergenerational transmission of economic status. *Journal of Political Economy*, *127*(2), 000-000.

Marrero, G. A., & Rodríguez, J. G. (2013). Inequality of opportunity and growth. *Journal of development Economics*, 104, 107-122.

Roemer, J. E., & Ünveren, B. (2017). Dynamic equality of opportunity. *Economica*, *84*(334), 322-343.