Endogenous Skills and Labor Income Inequality

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24 January 2018

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Abstract

How much does inequality in life depend on conditions established at age 18? What role does post-18 higher education play? I use an education choice model with exogenous conditions from family wealth, established human capital at age 18 and shocks to human capital to examine these questions. Family wealth and established human capital at age 18 determine the post-18 education choices. Education builds up human capital and reduces future earnings volatility. Absent this transmission channel, previous studies dramatically underestimate the importance of initial family wealth in explaining lifetime earnings inequality. My model finds that family wealth at age 18 explains up to 15% of lifetime earnings inequalities, and human capital at age 18 explains 72%. Policy counterfacutals that encourage college education by providing financial aid reduce inequality and improve welfare.

JEL classification: D31, D91, J24, J31.

Keywords: Lifecycle inequality, college enrollment, human capital accumulation, idiosyncratic uncertainty, general equilibrium, heterogeneous agents, quantitative macroeconomics.

*I am extremely grateful to my adviser Sanjay K. Chugh for his guidance and support. I am also indebted to Pok-Sang Lam and Bruce Weinberg for their invaluable advice. This paper benefited from discussions with Ryan Chahrour, Paul Chan, Hongyu Chen, Mikhail Golosov, Jaroslav Horvath, Felicia Ionescu, Basant K. Kapur, Fang Lei, Pascal Michaillet, Tristan Potter, Vincenzo Quadrini, Tony Smith, Stephen Terry, Ivan Vidangos, Youzhi Yang, Zheng Yu, and my classmates and seminar participants at the Ohio State University, the 32nd Annual Congress of the European Economic Association (EEA) and the 70th European Meeting of the Econometric Society (ESEM) in Lisbon and Asian Meeting of the Econometric Society in Hong Kong.

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1 Introduction

Individuals differ across many dimensions and respond to life-cycle earnings dynamics differently. The aggregation of such heterogeneous responses in consumption, labor supply, and human capital investment generates inequality across individuals and yields important macroeconomic consequences. Despite the large body of literature that identifies patterns and sources of life-cycle earnings inequality, surprisingly little research provides mechanisms that endogenously generate heterogeneous life-cycle earnings dynamics. With only patterns and sources exogenous to a model, the literature is largely silent on policy recommendations that aim at reducing the resulted inequality and raising welfare. This paper aims to fill this gap by identifying an endogenous channel of transmission from differences in human capital and family wealth at age 18 to life-time earnings inequality through choices of timing and extent of higher education.[1]

This study provides four theoretical and empirical contributions to the existing literature. First, I introduce endogenous education decisions through life-cycle to an overlapping generations model. This feature reveals the role of education on the transmission from exogenous conditions to lifetime earnings inequality. Second, the study identifies *ex-ante* and *ex-post* household responses in human capital investment to risk. Risk averse individuals invest in education raising human capital in lump-sum to reduce future earnings fluctuations. After severe negative shocks, one returns to school for further education and hence skill upgrading. Third, I quantify sources of lifetime income inequality, grounding my estimates in the empirical joint distribution of human capital and family wealth at age 18 as the initial condition. This method provides a stronger identification than the calibration strategy in literature following Huggett, Ventura, and Yaron (2011). Fourth, I evaluate policies designed to mitigate the impact of early life conditions on life outcomes, which previous studies have not done.

[1] In this paper, higher education includes all formal educations from college and beyond, such as college education, master degree programs, professional degree programs and PhDs. Later in the paper, I refer to higher education interchangeably as school education or college education. But degrees such as BA or MA are specifically referring to Bachelor's Degree or Master's Degree.

The study begins by providing novel empirical evidence of intermittent life-cycle education profiles. Different to the consensus under the Mincer et al. (1974) - Ben-Porath (1967) - Becker (1994)/Card (1994) tradition, individuals frequently move back and forth between school and work throughout their life. These patterns can be predicted by their family income and human capital stock at age 18. In light of this evidence, I propose a new model of higher education choices and examine how they transmit early age differences through the life-cycle. My model builds on a standard heterogeneous life-cycle overlapping generations household framework, but adds the following three features: (i) households can accumulate human capital through time devoted to work (learning on the job) and through schooling; (ii) households move between a production island and a leisure island when choosing their time discretely in labor supply, college education, and leisure, as in Krusell, Mukoyama, Rogerson, and Şahin (2011); and (iii) the main source of life-cycle earnings risk comes from the idiosyncratic human capital productivity shock to working individuals, similar to the structure in Huggett et al. (2011).

After calibrating the model to the U.S. data, channel decomposition shows that initial human capital explains over 70% of lifetime earnings inequality, in line with the literature. However, initial family wealth condition explains up to 15% variation in lifetime earnings, which is three times larger than the 5% documented by Huggett et al. (2011). This contrast arises due to the costly nature of college education in my model with endogenous college enrollment. Albeit building up human capital, attending college not only bears an extensive margin opportunity cost of giving up at least half of (if not all) working time, but also a fixed tuition cost. An individual's wealth condition determines the willingness to pay for and the affordability of school. Therefore some of the variations in the accumulated lifetime human capital is due to variation in initial wealth. Huggett et al. (2011) does not account for this channel, and therefore underestimates the variation in lifetime earnings attributable to variation in initial wealth.

In the model, life-cycle risk perturbs human capital and exacerbates earnings volatility. Risk averse individuals self-insure by accumulating human capital through enrolling in schools. Quantitatively, rising uncertainty and risk aversion lead to a higher college enrollment. Lifetime inequality rises by 6% after turning off college enrollment choice from the model.

Given the risk-dampening quality of college education, the model also predicts a tight relationship between initial conditions and lifetime earnings position in the presence of higher education choices. In addition, comparing individuals with and without a BA degree in the model, those with BA show higher upward social mobility.

Finally, I use the model to evaluate policies that affect the education decisions in order to modify the impact of exogenous conditions on inequality. Existing studies do not account for the endogenous transmission mechanism between exogenous conditions and lifetime earnings inequalities and thus cannot evaluate policy alternatives to reduce inequality (Huggett et al., 2011; Heathcote, Storesletten, and Violante, 2005). To the best of my knowledge, this is the first study that evaluates policies intended to change the impact of exogenous sources on life-cycle earnings inequality in a general equilibrium context. In particular, government-provided scholarships that allow low-income students to attend college reduce lifetime earnings inequality by 7%, increase aggregate labor productivity, and raise consumer welfare. A similar policy subsidizing the college education of the highest human capital quintile students achieves similar results, but with smaller consumer welfare improvement.

The remainder of the paper is organized as follows. Section 2 documents new empirical facts that motivate the theoretical model. Section 3 develops the theoretical model and characterizes the mechanism of college education decisions. Section 4 provides calibration results. Section 5 establishes the quantitative relationship of education to the transmission of initial conditions to life-cycle earnings inequalities. Section 6 evaluates policies that impact such transmission channels. Section 7 concludes.

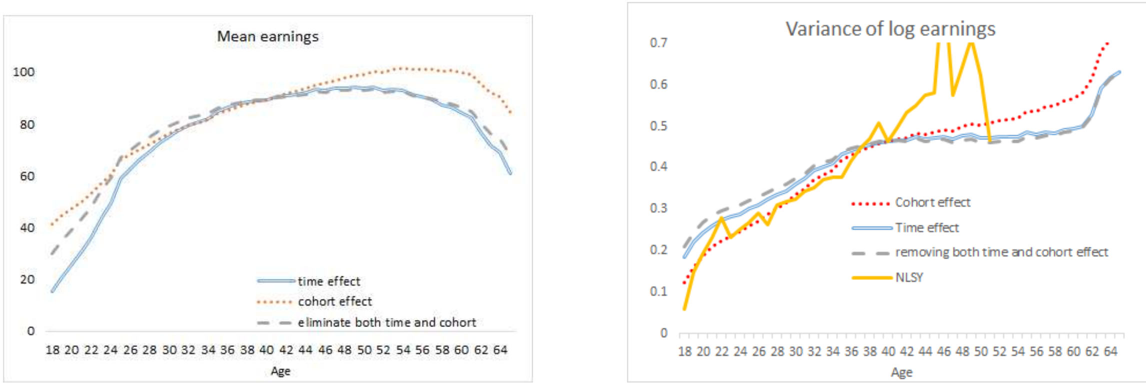
2 Empirical Support

In this section, I document two empirical findings, life-cycle earnings profile and life-cycle education profile, that provide support and motivation for the rest of the analysis and provide targets for the benchmark model calibration.

2.1 Life-cycle earnings profile

I use the Current Population Survey (CPS) data to construct synthetic cohorts in describing a household's life-cycle earnings profile. Specific data selection criteria follow Huggett et al. (2011). In particular, I select data from 1976 to 2016 for individuals between age 18 and 60. Those with annual labor earnings below $4900 in 2009 dollar value, those with top-coded income, and those who work less than 260 hours a year are dropped. The time effect and cohort effect are removed to reveal the underline information about earnings profile. Individuals group together based on age-year-cohort characters. Each variable of concern is generated from the within group value of the variable. For example, the mean of earnings comes from the mean of annual wage for each age-year-cohort group. To remove the time and cohort effect, I generate dummies for each year, age, and cohort and then run OLS regression of the variable on the dummies. The coefficient selected from each age dummy provides an underline age profile of the variable. In order to provide comparison to Huggett et al. (2011), I describe data into cohort effect and time effect, as well as removing both. Figure 1 describes the age-earnings profile.

In Figure 1, Panel (a) provides results for the mean earnings of each age. The mean earnings profile adjust to make sure that all the series cross at age 40. All series are normalized according to having the mean wage to be 100 at age 60 from the cohort effect series. All three series show a similar hump-shaped age-earnings pattern, with a peak at around age 54. There is a sharp growth of earnings between age 18 and age 24, and the peak earnings about triple the initial earnings at age 18. Upon retirement, the earnings drop about 22%



(a) Mean earnings using CPS data

(b) Variance of earnings using CPS and NLSY79 data

Figure 1: Lifecycle earnings profile

from the peak level.

In Figure 1, Panel (b) describes the earnings volatility across ages. All series are adjusted to cross at age 40. It shows a growing earnings inequality from initial age at around 0.2 to above 0.6 at the retirement age. In addition to the information from CPS, I include data from NLSY79. Since NLSY79 has the longest panel with details in earnings and education related information, certain targets for this study rely upon NLSY79. Comparing the second moment of earnigs from NLSY79 to CPS provide a validity check of NLSY79 in its level of representation, as provided in Panel (b). Prior to age 40, variance of earnings from NLSY79 fits the CPS trends well. But after age 40, it starts to deviate. This is mostly due to the loss of respondents in recent years. For the purpose of calibrating education related targets using NLSY79, pre-40 information was the most important (as explained in the next section). Hence the post-40 deviation doesn't impact the descriptive power of the data for the purpose of finding relationships between education and earnings inequalities.

2.2 Life-cycle education profile

Empirical evidence shows that there is a significant amount of moving between the labor market and school. In this study, I restrict schooling as formal credited degree-granting collegiate education. The degrees include BA, MA, PhD, and professional degrees.

Panel (a) and (b) in Figure 2 use the CPS and Annual Social and Economic Supplement (ASEC) samples to describe the life-cycle higher degree attainment profile. In Panel (a), I select data from 1962 to 2016 to construct a synthetic age cohort. Each age cohort includes individuals within a 5-year interval. For example, the 1962 cohort includes all individuals between age 20 and 25 at the year 1962; the 1967 cohort includes all between the ages of 20 and 25 at 1967. I calculate the percentage of the sample with at least a college degree for each cohort as it ages. Except for the 1972, 1977, and 1982 cohorts, which have some crossings as they age, the rest of the cohorts show three cohesive patterns: first, each younger cohort has a higher college attainment rate across all ages than the previous cohort. Secondly, along each cohort, more people obtain college degrees at a latter age. Thirdly, younger cohorts have a higher tendency to return to school at a later age than older generations.

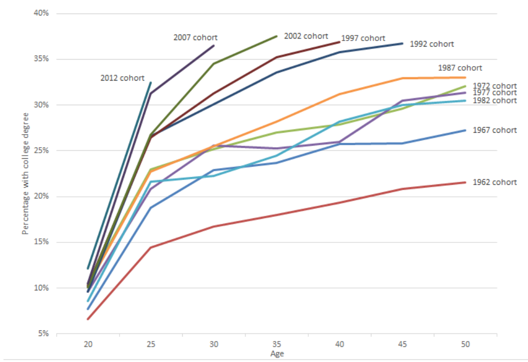
I remove time and cohort effect as in Figure 1 and display the underline age-education profile in Panel (b) of Figure 2. Each series indicates the maximum degree one obtains at a given age. As the age increases, all series increase except for the ones with some college. More individuals with only some college degree move to obtain a BA and above. Despite more individuals obtaining advanced degrees, the share with only BA stays roughly constant with slight improvement. This shows that the share of individuals progressing from BA to more advanced degrees roughly equals the share of individuals obtaining a BA as age increases. From age 22 to age 64, the share of the sample with college experience and above increased from 50% to 70%.

Increasing degree attainment across cohorts and age indicates that we have a significant number of people enrolling in collegiate education throughout the life-cycle. The collegiate education decision is not just inter-generational, as most studies suggest, but also intra-generational.

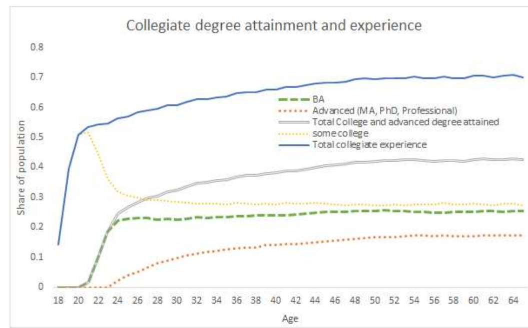
Panel (c) of Figure 2 directly describes the life-cycle college enrollment behavior from the National Longitudinal Survey of Youth 1979 (NLSY79) [2]. Panel (c) tells a similar story.

[2]NLSY79 is the uniquely available nationally representative longitudinal survey that spans respondents from age 14-22 to age 51-58, almost the entire working life, thereby providing complete details of hetero-

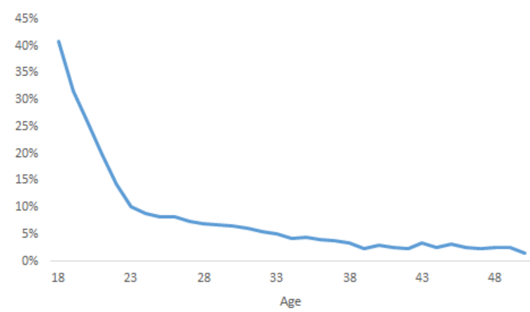
Although the ages with the largest shares of individuals enrolling in college are younger than 23, a decreasing but still significant number of individuals enrolled are in schools even beyond age 40. Given the importance of education, this ”irregular” intermittent higher education decisions should not be overlooked in macro studies.



(a) College attainment by cohort



(b) Degree attainment by age



(c) College enrollment by age using NLSY79

Figure 2: Lifecycle degree attainment/enrollment

Table 1 describes the data from NLSY79. Of the entire sample, 21% completed a bac-

geneous decision-making information to discipline this study. Following Light (1995a) and Light (1995b) in constructing the panel from NLSY79, I select sample year from 1979 to 2010. I restrict the sample to respondents younger than 20 years old by 1979, the starting year of the survey. I exclude those without AFQT scores, a key variable for further comparisons. Due to the enormous inconsistency in degree reporting, high school graduation is loosely defined if one has a high school diploma or by the retrospective variable, the highest degree completed between 11 and 13 years of education, if one did not report high school degree information. I use monthly college enrollment and current enrollment information to trace one's college enrollment and stop-out/dropout history[3]. Since I only consider formal school enrollment, less than 5 months of enrollment each year is excluded from ”enrolled in the year”. I further use reports on college enrollment, retrospective and ongoing highest degree completed variables, full/part time college enrollment, and college enrollment history to cross validate each person's college enrollment history. I only consider 4-year college and above as having a college degree and do not differentiate 2-year degrees from the rest of college dropouts. This is a reasonable simplification. According to Athreya, Eberly, et al. (2013), 4-year college degree wage premium is 1.74 over high school, while premium of some college is only 1.2. Similarly, Kane and Rouse (1995) report a 2-year college degree premium of about 1.1.

calaureate degree, and 51% have at least one year of college, among which 67% have some interruptions before finishing a baccalaureate degree. Another 58% of the sample may or may not have started college, but left school entirely before receiving a baccalaureate degree by 2010. Only 8% of the sample completed college in four years from right out of high school [4]. With the exception of the 47% of the sample who completed high school and never return to school and the 12% of "regular" students, the rest experience delayed college entry and/or episodes of interruptions in their higher education experience. Together, about 42% of the sample presents as a special target of interest for this study [5].

Across different groups in Table 1, several mean differences stand out. First of all, there is a positive correlation between AFQT (Army Forces Qualification Test) score and college entrance and completion. "Traditional" students have the highest average AFQT score. Returners have the second highest, and all who dropped out of school before receiving a baccalaureate degree have the lowest AFQT. Though not perfect, AFQT is widely regarded as an approximation to one's ability [6]. Secondly, net family income varies systematically too. For younger agents, net family income mainly refers to net income of their parents; for older ones, it is mostly their own net household income. Again, traditional students have the highest net family income at age 18, while delayers have the lowest. Dropouts before completing BA have a lower net family income, and returners other than delayers have higher income. Together, they suggest that human capital and wealth heterogeneity matters. Table 2 displays mean statistics in comparing factors that may impact individuals at the time of dropping out and at the time of returning to school. It gives more descriptive statistics,

[4] Light (1995a) documents 2/3 of her sample completed education in one setting, including both high school and college, among which 12% completed BA. It gives 8% of her sample completing the college degree in one setting without waiting. Same statistics can be reflected from CPS education attainment information by cohort

[5] In Table 1, returners are all those who have had some interruptions before finishing a baccalaureate degree and who have returned to school at least once. Delayers, a subset of returners, are all of those who delayed entry to college after high school graduation. Non-returners are all of those who quit school at one point since high school graduation and have never been observed to re-enroll in school until 2010. Traditional students are all of those who finished their college degree right after high school and without any interruptions. They are a subset of non-returners

[6] For the rest of this paper, I use innate ability, human capital, and labor productivity interchangeably, since they matter the same way to labor earnings in the model

Table 1: Descriptive Statistics

	Total sample	Returner		Non-returner		
		All returner	Delayer	All non-returner	Dropout before BA	Traditional students
Sample size	6945	2381	1149	4564	3997	567
AFQT	40.25	47.9	39.34	36.26	31.77	67.94
	(27.19)	(27.15)	(24.08)	(26.32)	(23.37)	(24.13)
Net family income	49172.79	52054.43	40551.76	47407.48	43670.79	67083.38
	(39879.25)	(40959.8)	(34068.14)	(39105.45)	(36170.8)	(47254.72)
Log Wage rate	1.96	1.95	2.01	1.97	1.97	1.96
	(0.69)	(.65)	(0.60)	(0.71)	(0.72)	(0.65)
Hours worked	907.45	865.02	1005.16	932.88	986.62	646
	(770.67)	(739.26)	(842.27)	(787.91)	(820.91)	(490.12)
% Married	36.49	34.61	44.21	37.46	40.03	19.4
% Have children	29.81	27.13	38.73	31.2	34.83	5.64
Highest grade completed	13.52	14.92	13.79	12.79	12.26	16.48
	(2.08)	(2.22)	(1.53)	(1.57)	(0.68)	(1.05)
% completed BA	21.32	38.39	13.93	12.42	0	100
% with college experience	51.35	100	100	28.2	18.01	100
Black	27.44	28.64	29.33	26.82	28.2	17.11
Hispanic	15.75	16.8	20.19	15.2	16.06	9.17
Other race	56.80	54.57	50.48	57.97	55.74	73.72
Woman	50.66	57.87	58.57	46.89	47.06	45.68

Note: Net family income, log wage rate, hours worked, are at age 18, marriage status, number of children are at age 23.
Parenthesis reports standard deviation.

showing the different financial positions for individuals at the time of leaving school and at the time of returning to school. All in all, financial and individual human capital are tied to collegiate education decisions. Meanwhile, other random factors, such as family obligations, may impact one's decision as well. These observations provide crucial empirical supports for the components in economic modeling in the following sections.

Table 2: Overview of interruption years and re-enrolling

	Delayers Mean		Other Returners Mean
Net family income			
Before high school graduation	38551.29	Before dropout	45664.34
	(34091.55)		(65418.06)
Before enrolling	49217.34	before returning	54377.16
	(71670.53)		(54005.85)
log Wage rate			
After high school graduation	1.98	after dropout	2.21
	(0.77)		(0.87)
Before enrolling	2.30	before returning	2.60
	(0.8)		(0.76)
after completion	2.20	after completion	2.18
	(1.24)		(1.04)
Spouse income			
Before enrolling	33635.22	before returning	26791.79
	(25783.78)		(24089.19)
after completion	29373.49	after completion	31135.3
	(35635.08)		(37689.84)
# children			
at enrollment	0.97	at return	0.99
	(1.18)		(1.22)
Age of youngest child			
at high school graduation	1.99	at dropout	1.35
	(2.92)		(2.67)
at enrollment	3.51	at return	4.41
	(4.37)		(5.46)

Note: Parenthesis reports standard deviation.

3 Model

In order to study the role of college education in life-cycle earnings inequality, the paper models human capital acquisition with foundations from a broad range of studies.

The traditional life-cycle framework implies that one attends school in the first phase of life, after which one supplies labor and only learns from working (Ben-Porath, 1967; Mincer et al., 1974; Rubinstein and Weiss, 2006). A small branch of research documents irregularities to this framework, where one experiences delays in attending college after high school or experiences college stop-outs, which are marked by periods of labor market experiences in between spans of college enrollment (Light, 1995a,b; Monks, 1997; Dynarski, 1999; Seftor and Turner, 2002; Johnson, 2013; Arcidiacono, Aucejo, Maurel, and Ransom, 2016). These observations support the endogenous life-time higher education choices in my model, in addition to the empirical evidence I present. At the core, the optimal human capital investment profiles should equate marginal rate of return to the opportunity cost of funds in all periods (Cunha, Heckman, Lochner, and Masterov, 2006). These studies also identify factors leading to college decisions, such as financial constraint (Ozdagli and Trachter, 2011; Johnson, 2013) and an individual's ability (Belley and Lochner, 2007; Arcidiacono, Bayer, and Hizmo, 2010; Stange, 2012). These studies form the theoretical and micro foundation for my modeling higher education decisions.

Lastly, the model considers three types of riskiness related to college education: completion risk (Hungerford and Solon, 1987; Bowen, Chingos, and McPherson, 2009; Athreya et al., 2013), expected return risk (Storesletten, Telmer, and Yaron, 2004; Lee, Lee, and Shin, 2014), and borrowing risk (Belley and Lochner, 2007; Ionescu, 2009; Rothstein and Rouse, 2011).

The model apparatus is constructed from a standard life-cycle overlapping generation model. Each model period is one year; households enter the model at age 19, retire at age 65, and live up to 75. One representative firm hires effective units of labor and rents capital from households to produce a single output. It extends beyond the standard model as follows.

First, individuals can make endogenous college education decisions at any age between age 19 and 65. Second, to capture the three types of risks associated with college education, I introduce the human capital productivity shock and a set of loosely-speaking job separation and job matching shocks. The human capital productivity shock follows Huggett et al. (2011) as the main source of earnings uncertainty. The job separation and matching shocks stem from Krusell et al. (2011), which provides an abstract to the expected college return risk. Third, the associated "islands" that come with the separation and matching shocks give a succinct but effective account to the flow among working, schooling, and non-working status. Fourth, households are allowed to borrow a non-default-able debt up to a borrowing limit at the tuition level. Such debt structure serves as a proxy to the education loan. Fifth, households are *ex-ante* heterogeneous on initial human capital and wealth, based on empirical evidence. Age provides an additional layer of *ex-ante* difference. *Ex-post*, education level, wealth, human capital, and labor market status differ after endogenous choices.

3.1 Households' problem

Every period, there are ω of new households entering the model and ω of them exiting the model. I normalize the total population to be one. Therefore, ω assigns value 1/57. Households maximize expected lifetime utility, given initial financial wealth s and initial human capital i.

Table 3 describes the timeline for households' life-cycle labor status decisions. From age 19 to 65, each individual chooses one of the four extensive status decisions e: working full time w, working part-time and schooling part-time pt, schooling full time sch, and leisure full time $nonemp$. After age 65, one retires and enjoys full leisure activities.

Two types of shocks, human capital production shock ϵ_w, which is realized only if one is working (full time or part time), and the loosely-speaking job separation and matching

Table 3: Life-cycle time-line

Real age:	19 – 65	65 – 75
Model age:	1 – 47	47 – 57
Discrete choices:	Work full time, part time and school part time, school full time, leisure full time	Retired

shocks λ and δ, arrive at households every period. All shocks are *iid* across individuals and time periods.

To accommodate the loosely-speaking job separation and matching shocks, households are located on either production island or non-production island. Figure 3 describes the islands and the associated extensive margin labor supply decisions. If located on the production island, one may choose to work full time, to work part-time and school part time, or endogenously decide to move to the non-production island. If located on the non-production island, one may only choose between full time schooling and non-employment. This decision is represented by $e = [w, pt, sch, nonemp]$

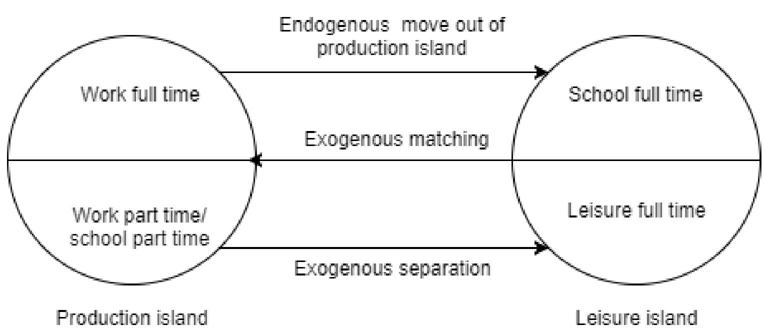


Figure 3: Endogenous and exogenous labor supply decisions

At the end of each period, those on the production island may receive a loosely-speaking job separation shock δ that exogenously moves them to the non-production island. In order to move back to the production island, households on the non-production island have to wait for a loosely-speaking job matching shock λ. Therefore, one may stay on the production island with a probability of $(1-\sigma+\sigma\lambda)$ if starting on the island, and a probability of $\delta(1-\lambda)$ that moves them to non-production island exogenously. If starting on the non-production island, one may be exogenously moved to the production island with probability (λ), and stay on the non-production island with probability $(1 - \lambda)$.

Equation 1 describes the extensive margin labor supply and human capital investment decisions. Households maximize lifetime value by choosing e given the beginning of the period location. V is the value if one is on the production island and V^2 if one is on the leisure island. $V^w, V^{pt}, V^{sch}, V^{unem}$ describes the value for one choice $e = [w, pt, sch, nonemp]$. At the final age, $age = 75$, $V_{age+1} = 0$. Since households face the same problems before retirement at every period, I omit the subscript for age in the following description of the model.

$$\begin{aligned} V(\phi; \mu) &= \max\{V^w(\phi; \mu), V^{pt}(\phi; \mu), V^2(\phi; \mu)\} \\ V^2(\phi; \mu) &= \max\{V^{sch}(\phi; \mu), V^{unem}(\phi; \mu)\} \end{aligned} \tag{1}$$

Households are also differentiated on how many years of post-secondary schooling one has completed yrs. Together, households are heterogeneous in the following idiosyncratic states: $\phi \equiv \{i, s, e, yrs, age\}$.

Based on their decisions, households evolve on each dimension of the idiosyncratic states every period. We have an endogenous aggregate state μ, a probability measure of households on each idiosyncratic state, generated by the open subset of the product space: $\Phi = \mathbb{R}_+ \times \mathbb{R}_+ \times \mathbb{Z} \times \mathbb{R}_+ \times \mathbb{Z}_+$.

If a household is on the production island and decides to work full time, the household chooses consumption and savings to maximize the lifetime value. The labor supply takes a stand from the indivisible labor framework (Hansen, 1985; Rogerson, 1988). The household supply a full unit of time to work and receives dis-utility of working $disu_{wft}$.

For working individuals, as in Equation 2, human capital accumulates through learning on the job. Human capital shocks ϵ_w perturb the learning efficiency. ϵ_w abstracts from various sources of factors impacting one's productivity, such as pregnancy, health, or other family-related factors as shown in the empirical section. ϵ_w is iid across individuals and time. But given its nature on i, a stock variable for human capital, the impact of ϵ_w is persistent.

One receives wage w paid to the efficient units of labor i and interest income rs. Every period, employed households pay social security tax at rate τ and lump sum income tax Υ. One may borrow a non-defaultable debt with borrowing limit $\underline{s}$.

$$
\begin{aligned}
V^w(\phi;\mu) = \max_{c,s'}\{u(c) - disu_{wft} \\
+\beta((1-\sigma+\sigma\lambda)V(\phi';\mu') + \delta(1-\lambda)V^2(\phi';\mu'))\} \\
\text{s.t.} \\
c + s' = (1+r_\mu)s + w_\mu i(1-\tau) + \Upsilon \\
i' = \epsilon_w A(i)^a \\
s \geq \underline{s}
\end{aligned}
\tag{2}
$$

If one chooses part-time working and part-time schooling, as in Equation 3, one receives disutility from working and from schooling. The human capital accumulates through both learning on the job and schooling. Human capital shock ϵ_w still perturbs the efficiency of learning on the job. One receives half of wage w paid to the efficient units of labor i and pays half of the full time tuition κ.

$$
\begin{aligned}
V^{pt}(\phi;\mu) = \max_{c,s'}\{u(c) - disu_{wpt} - \psi^c(i,a,pt) \\
+\beta((1-\sigma+\sigma\lambda)V(\phi';\mu') + \delta(1-\lambda)V^2(\phi';\mu'))\} \\
\text{s.t.} \\
c + s' + \kappa/2 = (1+r_\mu)s + iw_\mu(1-\tau)/2 + \Upsilon \\
i' = i^\alpha(\epsilon_w A^\alpha + \Delta(yrs)^\alpha)/2 \\
s \geq \underline{s}
\end{aligned}
\tag{3}
$$

If an individual decides to go to school full time, as in Equation 4, the individual receives disutility $disu_{sch}$ from going to school, which is a function of the current level of human capital and age. Since schooling is located on the non-production island, one has to receive a job matching shock λ to relocate to production island in the next period. Otherwise, the individual will stay on the non-production island. Households' income only comes from previous savings (or debt) and tax transfer, which must be allocated among consumption, savings (or borrowing) for the future, and tuition payment κ. Human capital moves up by a scaling factor $\Delta(yrs)$, a function based on years of education. In summary, households have to pay a fixed tuition cost, psychic cost, and opportunity cost of current earnings in order to enroll in school. Hsieh, Hurst, Jones, and Klenow (2013) provides support for including both direct and indirect costs in education choices in order to generate asymmetric education investment behaviors.

$$\begin{aligned} V^{sch}(\phi;\mu) = \max_{c,s'} \{ & u(c) - disu_{sch}(i,a,ft) \\ & +\beta(\lambda V(\phi';\mu') + (1-\lambda)V^2(\phi';\mu'))\} \\ & \text{s.t.} \\ c + s' + \kappa &= (1+r_\mu)s + \Upsilon \\ i' &= (\Delta(yrs)i)^\alpha \\ s &\geq \underline{s} \end{aligned} \tag{4}$$

If an individual decides to stay at home, as in Equation 5, she faces a simple consumption-saving problem with full time to leisure (normalized to zero in comparison to disutility from school and working). One has to wait for a favorable λ next period for a chance to enter the production island. However, her human capital depreciates deterministically by δ_i portion every period.

$$\begin{aligned} V^{unem}(\phi;\mu) = \max_{c,s'} \{ & u(c) + \beta(\lambda V(\phi';\mu') + (1-\lambda)V^2(\phi';\mu')\} \\ & \text{s.t.} \\ c + s' &= (1+r)s + \Upsilon \\ i' &= (1-\delta_i)i \\ s &\geq \underline{s} \end{aligned} \tag{5}$$

After age 65, one retires from the labor market, as in Equation 6, and no longer chooses to attend school, but remains in a pure leisure mode. One receives social security benefit Ω and pays income tax Υ. It is a simple Huggett (1993) problem.

$$\begin{aligned} V^R(a, s; \mu) = \max_{c,s'} \{u(c) + \beta V^R(a+1, s'; \mu')\} \\ \text{s.t.} \\ c + s' = (1+r)s + \omega + \Upsilon \\ s \geq \underline{s} \end{aligned} \tag{6}$$

Standard concave utility qualities apply. In particular, $V^w, V^{pt}, V^{sch}, V^{unem}$ are concave in consumption c, hence $\frac{\partial V^e}{\partial y} > 0$, and $\frac{\partial V^e}{\partial y \partial y} < 0$, where $y \in \{s, i\}$. I parameterize the utility function as $u(c) = \frac{c^{1-\rho}}{1-\rho}$, $disu_w = \psi \frac{n^{1-1/\gamma}}{(1-1/\gamma)}$ and $disu_{sch} = \psi_{sch} \frac{age^p}{i^x} sch$. Risk averse households have value increasing in s, and in i.

3.2 Firm's problem

One homogeneous firm employs efficient units of labor and rents capital for final goods production as in Equation 7. Capital k comes from households' savings s'.

$$\Pi = zF(K, L) - wL - rK \tag{7}$$

Despite the "island" nature of the economy, the market operates competitively conditional on households' access to the labor market. This is similar to the argument by Krusell et al. (2011) and Lucas and Prescott (1974). Given the constant returns to scale production technology, firms pay price at competitive market rate: $w = MRL$, and $r = MRK$.

3.3 Stationary Equilibrium

A recursive competitive equilibrium is a set of functions: Let $x_a \in X_a$ denote age specific state space according to previous subsections, and $X_a \subset \Phi$. A stationary recursive competitive equilibrium is a collection of factor prices w, r, households decision rules $s_{a+1}(x_a)$,$i_{a+1}(x_a)$,$e_a(x_a)$,$c_a(x_a)$,$yrs_a(x_a)$, value functions $V_a(x_a)$ s.t.

1. Given w and r, individuals optimize individual's problems.
2. $w = F_2(K, L)$, and $r = F_1(K, L)$.
3. r and w are paid (constrained) competitively and clear markets:

$$L = \sum_{a=18}^{65} \sum_{yrs=0}^{10} \int_{X_{a,yrs}} (i(x_{a,yrs,e=w}) + \frac{1}{2} i(x_{a,yrs,e=pt}))\mu(x_{a,yrs})d\zeta$$

$$K = \sum_{a=18}^{65} \sum_{yrs=0}^{10} \int_{X_{a,yrs}} s(x_{a,yrs})\mu(x_{a,yrs})d\zeta + \sum_{a=66}^{75} \int_{X_a} s(x_a)\mu(x_a)d\zeta$$

4. Government balance budget: $G + \omega \sum_{a=66}^{75} \int_{X_a} \mu(x_a)d\zeta = w\tau L - \Upsilon$, where $G \geq 0$
5. Individual decision rules for firms and households are consistent with the aggregate law of motion, Γ, where $\mu' = \Gamma\mu$

3.4 Model mechanism

3.4.1 Human capital and school

This paper falls under the general literature of identifying income dynamics and how households respond to risk by adjusting labor, consumption, and human capital investment decisions. There are two types of risk in the model that formulate the exogenous foundation of life-cycle earnings dynamics: human capital production risk ϵ_w and the loosely-speaking job separation risk δ. For ease of illustration, I rename the future value of i when one chooses to work in the current period as i'_w and as i'_{sch} if one chooses school in the current period. Despite it being extensive, δ averages out across population and time. Human capital production risk serves as the main source of earnings uncertainty.

Proposition 1 provides theoretical evidence for an *ex-ante* response to ϵ_w, and Proposition 2 provides evidence for an *ex-post* response.

Proposition 1.

For any given set of $\{s, i, age, c, yr, e, \Upsilon, \tau, \mu, \epsilon_w\}$, $i'_1 > i'_2$ *implies* $Var(\frac{\partial V}{\partial i'_1}) < Var(\frac{\partial V}{\partial i'_2})$.

Proof. See Appendix A.1 □

Proposition 1 provides theoretical evidence on the insurance quality of higher education to future earnings fluctuations due to the arrival of ϵ_w that causes fluctuations in i. Proposition 1 states that the higher the human capital one accumulates, the less fluctuation one receives in the marginal value of human capital i, which insures a smoother life-cycle consumption profile. The fastest way to accumulate human capital is through college education. Since households are risk averse due to the concavity of utility function, they prefer attending schools at an early age. As such, this is an *ex-ante* response to future ϵ_w.

Proposition 2.

1. *There exists a threshold for* $\frac{age^p}{i^x}$, $\frac{\bar{age^p}}{i*^x}$ *where for a fixed set of* $\{s, c, yr, e, \Upsilon, \tau, \mu\}$, *s.t. for* $\frac{age^p}{i^x} > \frac{\bar{age^p}}{i^x}$, $V^w > V^{sch}$. *For* $\frac{age^p}{i^x} \leq \frac{\bar{age^p}}{i^x}$, *there exists a threshold for* i'_w, $\bar{i'_w}$, *such that if* $i' > (<)\bar{i'_w}$, $V^{sch} < (>)V^w$, *and with equality if and only if* $i' = \bar{i'_w}$.
2. *There exists an* $\epsilon_w > 1$, $i'_w > \bar{i'_w}$; *and an* $\epsilon_w < 1$, $i'_w < \bar{i'_w}$.

Proof. See Appendix A.2 □

Part 1 of Proposition 2 establishes the relationship between the current human capital level and the choice of enrolling in school. Households consider three factors in deciding whether to enroll in school for the period: disutility of schooling, human capital return from schooling and opportunity cost of schooling. Disutility of schooling is negatively related to the level of human capital. Returns from schooling on human capital comes from the existing level of human capital i and the efficiency of learning in school Δ. The higher i is, the higher return to schooling is. The opportunity cost, on the other hand, is the earnings and learning-on-the-job one forgoes. The higher i is, the more opportunity cost it is. The returns to human capital from schooling and the level of opportunity cost creates a threshold $i*_1$. For $i > i*_1$, the opportunity cost dominates returns from schooling, hence one prefers working; vice versa. The disutility also creates a threshold $i*_2$, such that if $i < i*_2$, households would experience too much disutility to attend school, regardless of the returns and opportunity cost.

Figure 4 describes the mechanism. In Panel (a), $i*_1 > i*_2$; disutility cost from schooling is low. In Zone A, where disutility of schooling is too high, one would not choose to go to school. In Zone B, opportunity cost of going to school is lower than the returns from school on human capital; one would choose school over working. In Zone C, the opportunity cost is too high, hence one would choose to work.

In Panel (b), $i*_1 < i*_2$; disutility cost from schooling is high. One would not choose to go to school at all if $i < i*_2$, as in Zone D and Zone E. In Zone F, even though disutility from going to school is smaller, the opportunity cost is too high. One would not choose school in Zone F.

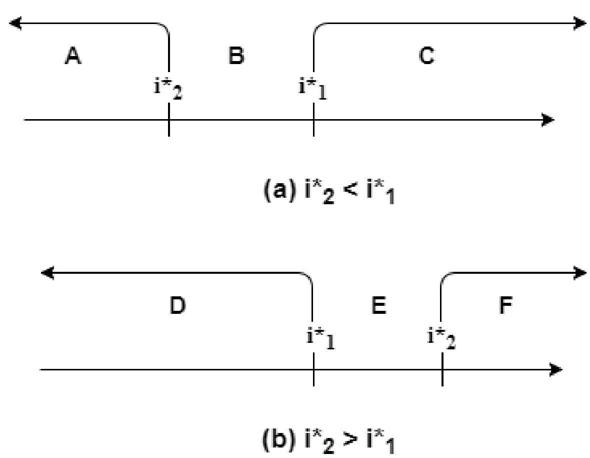


Figure 4: Human capital and school choices

According to Part 2, when facing a negative ϵ_w shock, those satisfying the threshold conditions (i.e., those who are younger or have sufficient existing human capital) may respond by enrolling in school; a high shock encourages working. This is due to the lower opportunity cost of sacrificing wages and learning-on-the-job after the negative ϵ_w shock. Therefore, as an *ex-post* response, one tends to go to school when facing unfavorable shock.

3.4.2 Wealth and school

In addition to the impact of human capital and ϵ_w to one's college education decisions, wealth s plays a role as well. This section provides intuition of the decision making between savings and school choices.

First of all, if wealth is sufficiently low, one cannot afford tuition cost κ; therefore, one would not attend school. In Figure 5, Zone A, D and E falls under the case where one cannot afford enrolling in school.

Secondly, if school is affordable, one may also decide based on the opportunity cost in earnings and wealth accumulation in deciding whether to pursue college education. In other words, households decide which investment method is more efficient: investment on wealth or investment on human capital.

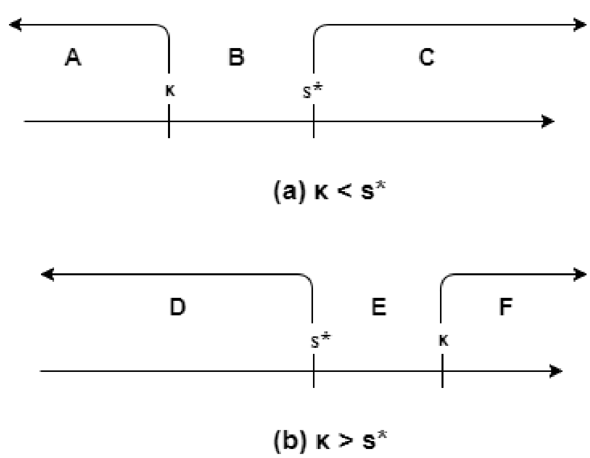


Figure 5: Wealth and school choices

Going to school has the budget constraint, with fixed $\{s, i, age, c, yr, e, \Upsilon, \tau, \mu, \epsilon_w\}$:

$$s'_{sch} = (1+r)s - \kappa - c + \Upsilon,$$

while going to work has

$$s'_w = (1+r)s - c + wi(1-\tau) + \Upsilon,$$

a higher wealth status for the next period, $s'_w > s'_{sch}$. If one has $s < s*$, a low wealth state in the first period, the marginal utility to consumption is high. Households values working more than schooling. This is reflected in Zone A, B, and D in Figure 5.

However, if the household has $s > s*$, a higher level of wealth, one would choose between the returns to schooling and returns to savings. If choosing to attend school in the first period and to work in the second period, the second period budget constraint is

$$c'_w = (1+r)s'_{sch} - s'' + wi\Delta(1-\tau) + \Upsilon,$$

compared to selecting to work in the first period,

$$c'_w = (1+r)s'_w - s'' + wi^a A\epsilon_w(1-\tau) + \Upsilon.$$

The wage received is higher in period two if going to school in period one, $wi\Delta > wi^a A\epsilon_w$. Given the stock nature of s and i, the difference to savings in the two periods between working and schooling generates lasting differential in one's lifetime utility. If the increase in lifetime utility that results from increased wage income in the future periods dominates the loss of savings due to paying tuition and not working, attending school is preferable; otherwise, working is preferable. This is reflected in Zone C and F in Figure 5.

4 Calibration

Table 4 and Table 5 list parameters for the benchmark model. Parameters in Table 4 are externally selected while those in Table 5 are jointly calibrated after solving the stationary equilibrium model to match the U.S. data moments. I report the targeted moments from data and from the model in Table 6, Table 7, and Figure 7 for a comparison of model fit. Figure 8 and Figure 9 report untargeted earnings profiles and detailed education profiles.

4.1 Parameter assignments

Table 4: Parameters externally determined

Parameter		Description
Initial conditions		
$E(i_0)$	2.4266	Mean initial human capital distribution
$std(i_0)$	0.8005	Std of initial human capital distribution
$E(s_0)$	2.6391	Mean initial wealth distribution
$std(s_0)$	2.0474	Std of initial wealth distribution
cov(s,i)	0.4188	Covariance of initial human capital and wealth
Tax system		
τ	0.106	social security tax rate, Huggett et al. (2011)
Ω	0.4	social security income as a share of mean 65 earnings, Huggett et al. (2011)
Preference		
γ	0.4	Frisch elasticity
ρ	2	Intertemporal elasticity of substitution
Others		
δ_i	0.02	Depreciation of human capital, Huggett et al. (2011)
α	0.64	Labor share of income

Preferences:

Households value consumption and leisure. I use a standard additive separable CRRA preference, with utility from consumption as $U(c) = \frac{c^{1-\rho}}{1-\rho}$. In the benchmark model, I select the risk aversion ratio ρ to be 2, a standard value used in macro literature, as in Huggett et al. (2011) and Browning, Hansen, and Heckman (1999). If one chooses to work, one receives dis-utility from working as $disu_w = \psi \frac{n^{1+1/\gamma}}{1+1/\gamma}$. $n = 1$ is for full time working, and $n = 0.5$ is for part time working. I assign γ, the Frisch elasticity, to be 0.4 for the benchmark model, which lies in the broad range of estimations in literature as reviewed by Chetty, Friedman, Olsen, and Pistaferri (2011).

If one chooses schooling, $disu_{sch} = \psi_{sch} \frac{age^p}{i^x} n_{sch}$, with $n_{sch} = 1$for full time schooling and $n_{sch} = 0.5$ for part time schooling. The disutility of schooling is positively related to age and negatively related to one's existing stock of human capital. These features are intended to capture the period-sensitivity and self-productivity of human capital accumulation. In other words, the older one gets, the more difficult it tends to be for one to study, but the more knowledge one has, the easier it is for one to gain further knowledge [7].

Parameter ψ is one key variable to determine the employment to population ratio, along with the efficiency of learning on the job and labor market frictions. Similarly, ψ_{sch} determines the enrollment to population ratio and overall levels of education attainment across all ages. Parameters p and x assign weighting to the utility cost on age and human capital stock to the college enrollment. Together, they govern the enrollment profile by age.

Human capital:

Human capital can move along three trajectories: accumulating on the job (or loosely speaking, "learning" on the job), learning in school, and depreciating while enjoying full leisure. A and a govern the rate of return to learning on the job; Δs govern the efficiency of schooling; and δ_i governs the loss of productivity from non-employment. To build in the "sheepskin" effect of education (Hungerford and Solon, 1987), I separate degree effects from intensive margin schooling. One receives Δ_1 for each year of college education before graduation and receives Δ_2 for the last year before receiving a college degree. If one continues beyond four years of college, each additional year of post-college school training gives her Δ_3 on her human capital, with an emphasis on a graduate degree as Δ_4 for the effect from the last year of graduate school. If one continues on to more schooling, one receives Δ_5 per year afterwards. There is a maximum total of ten years of collegiate education to choose

[7] For a comprehensive account of labor literature on lifecycle human capital production, refer to Cunha et al. (2006)

Table 5: Parameters determined internally using Simulated Method of Moments

Parameter		Description	Functional form
Preference			
β	0.9985	discount factor	$U(c)=\frac{c^{1-\rho}}{1-\rho}+disu$
ψ	2.6	disutility of working	$disu_w=\psi\frac{n^{1-1/\gamma}}{(1-1/\gamma)}$
ψ_{sch}	0.03	disutility constant of schooling	$disu_{sch}=\psi_{sch}\frac{age^p}{i^x}sch$
p	2.5	degree of disutility in age	
x	2.45	degree of disutility in human capital	
Human capital			
a	0.95	curvature of human capital investment	
efficiency of human capital accumulations:			
A	1.6714	on the job	$i'=\epsilon_w(Ai)^a$
Δ_1	1.0002	from school for some college	$i'=(\Delta_{yrs}i)^a$
Δ_2	1.5586	from school for BA	
Δ_3	1.0003	from school for post college education	
Δ_4	1.0224	from school for master degree	
Δ_5	1.0002	from school for more advanced schooling	
κ	0.8498	direct schooling cost	
Labor market frictions			
σ	0.0856	probability of job destruction	
λ	0.5368	probability of job matching	
Shocks			
$[\epsilon_h,\epsilon_l]$	[1.1535, 0.8465]	human capital accumulation shock	

from. The Δs are calibrated to match the cumulative degree attainment profile and the relative wage premium on education attainment. I define college experience premium as the ratio of end-of-life earnings of someone with college experience to those of someone without college experience. Similarly, A also helps to match the pure experience premium, defined as the ratio of mean end-of-life earnings to starting age earnings for people without college experience. Parameter δ_i is used to identify the average depreciation rate of human capital of 2% annually (Huggett et al., 2011). The direct cost of schooling κ impacts school enrollment decisions. It is also calibrated to match the total post-secondary education spending as, on average, 2% of the share of GDP (US Department of Education, 2016).

Tax system:

Government imposes social security tax on all working individuals before the retirement age of 65 and transfers a common income to retirees post-65 at lump-sum. I follow Huggett et al. (2011) for the tax system. Social security tax imposes at a rate of 0.106; social security benefit provides a common transfer of 0.4 of mean end of working age income for all individuals. In order to balance the budget, the government transfers the budget balance in lump-sum to all citizens as Υ. For Υ being positive, it is a tax rebate, and for it being negative, it is an income tax.

Table 6: Individual annual labor flow status

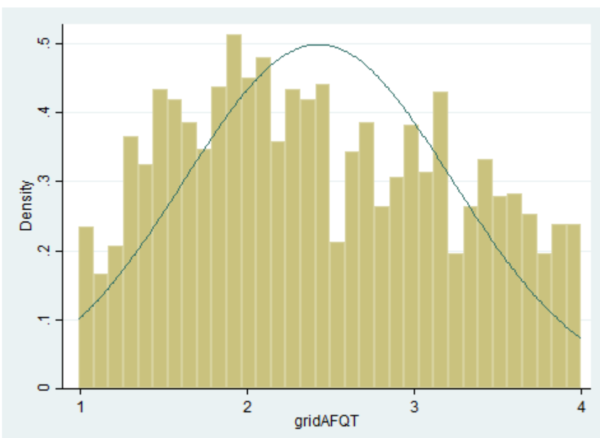
PSID					Model generated				
current/future	E	U	N	S	current/future	E	U	N	S
E	0.626	0.036	0.023	0.011	E	0.663	0.024	0.062	0.010
U	0.037	0.025	0.011	0.004	U	0.059	0.051	0.003	0.000
N	0.022	0.009	0.112	0.003	N	0.042	0.036	0.029	0.001
S	0.027	0.009	0.004	0.040	S	0.069	0.003	0.001	0.026

Labor market frictions:

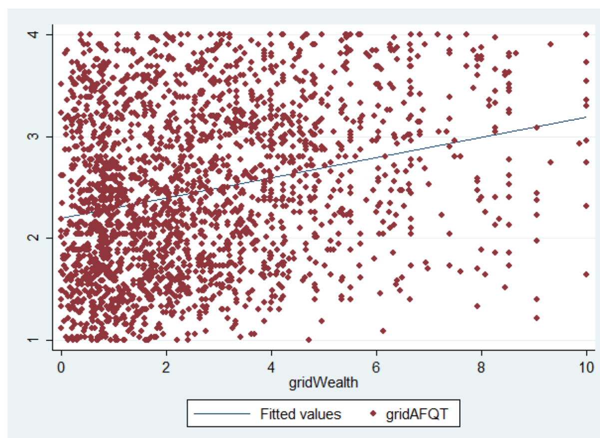
The loosely speaking, job destruction rate and job matching rate, exogenously move individuals between production island and non-production island. I follow Krusell et al. (2011) to match the flow labor status flow rate. Differently, I have schooling (S) as a separate status for households, along with employed (E), unemployed (U), and out of labor force (and not in school) (N). I use Panel Study of Income Dynamics (PSID) data from 1981 to 2013 to generate targets for annual labor flow rates as in Table 6.

Shocks:

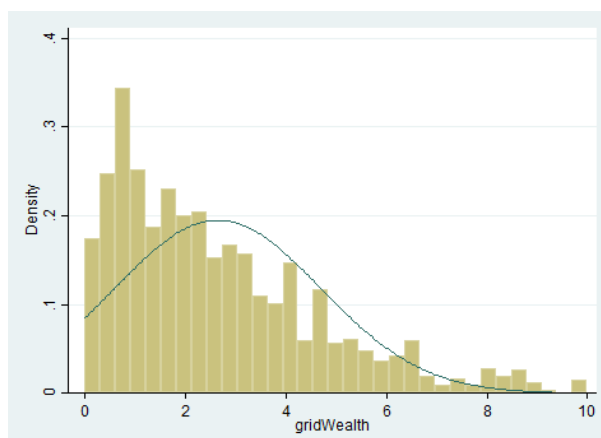
The earnings shock, ϵ_w, serves as the main source of variations to life-cycle uncertainty, as explained in the previous section. Similar to Huggett et al. (2011), ϵ_w follows an *iid* process across time and individuals, and it seeks to capture the risks that affect human capital production on the job. I calibrate two values of ϵ_w to impact the overall cross-sectional variations in earnings.



(a) Initial human capital distribution



(b) Correlation between initial human capital and wealth



(c) Initial wealth distribution

Figure 6: NLSY79 sample initial conditions

Net family income at age 18 in NLSY79 serves as a proxy to the household's initial family wealth background; AFQT scores serve as a proxy to the initial ability dimension. I re-scale the data level for both series into the model grid scale and directly map into the model as a joint normal distribution for the initial condition. Figure 6 Panel (a) and (c) plot distributions of both proxies, and Panel (b) plots the correlation.

Table 7: Additional targeted statistics from U.S. data and model-generated data

Target statistics	data	model
Annual risk free interest rate	0.041	0.047
Average annual post-secondary spending as a share of GDP	0.02	0.02
Cross-sectional variance of log wage	0.5553	0.4446
Employment to population ratio	0.6	0.7
Enrollment to population ratio	0.1-0.2	0.1
mean(Wage 65/ Wage 25) for high school only	1.126	1.117
mean(wage w college/wage without college)	1.75	1.60
Fraction with at least 4 years of college at age 65	0.4257	0.4076
Fraction with some college at age 65	0.2748	0.2974
Fraction with more advanced degrees at age 65	0.1723	0.1572
Fraction without college experience at age 65	0.299	0.295
Fraction of regular college students (fraction of BA at age 22)	0.018	0.004

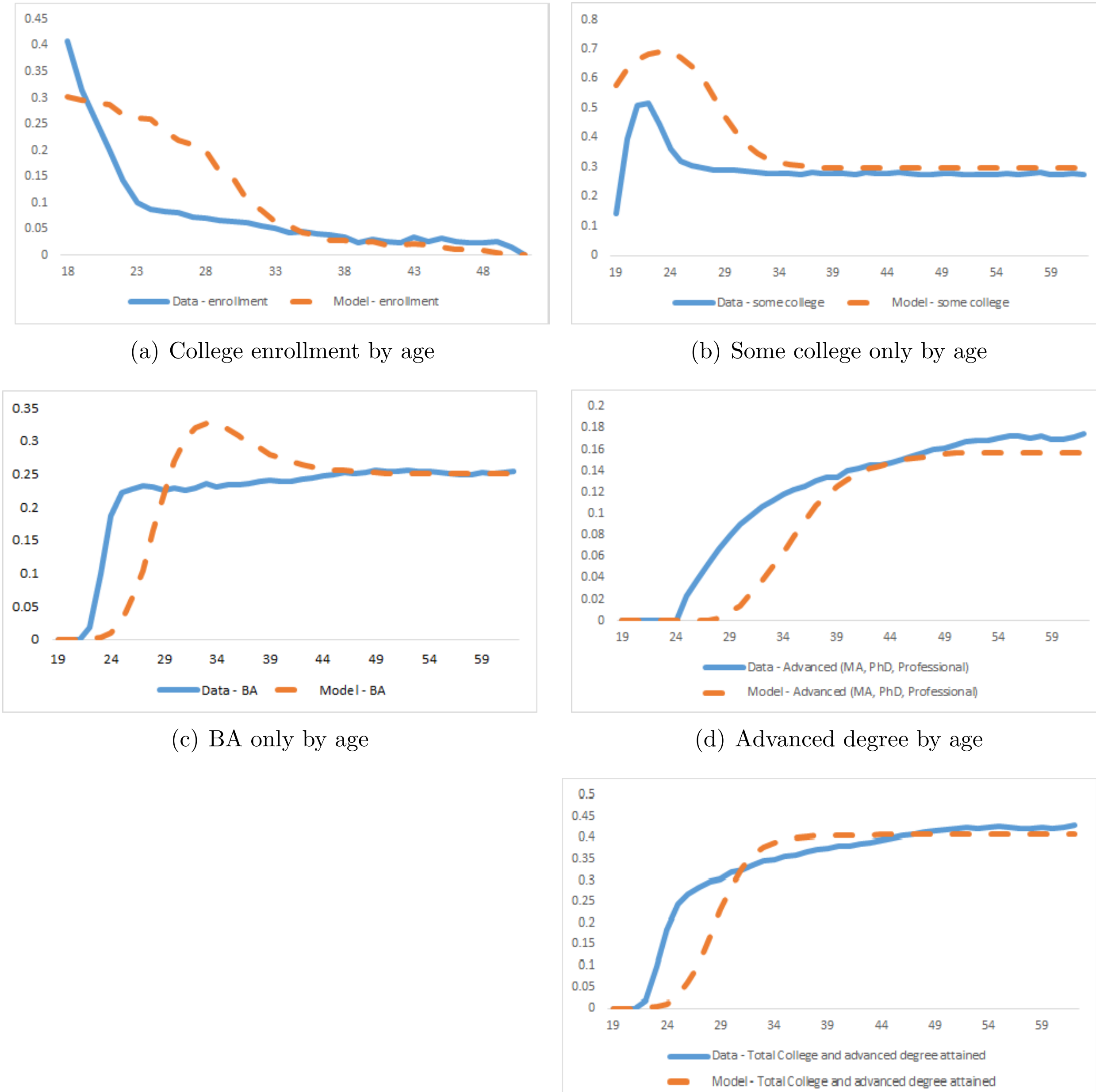
4.2 Model fit

Table 6 and 7 compare targeted moments between data and the model result. I simulate the stationary equilibrium rates for 5000 individuals over the life-time and obtain simulated data moments from it. Figure 7 serves as a comparison of the lifetime college education profile between data simulated moments.

Besides fitting the model to targeted moments, Table 8, Figure 8, and 9 provide an additional validity check of the model to untargeted moments.

Figure 8 describes life-cycle income and earnings volatility for households. Both model generated mean and variance of income follow the data well.

I further take the subsample of the simulated data with all who have college dropout and re-enrollment experiences and compare it with the NLSY79 data. Figure 9 provides a



(a) College enrollment by age

(b) Some college only by age

(c) BA only by age

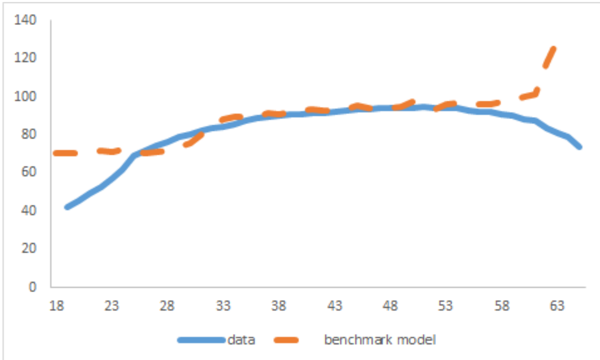
(d) Advanced degree by age

(e) Total college degree and above by age

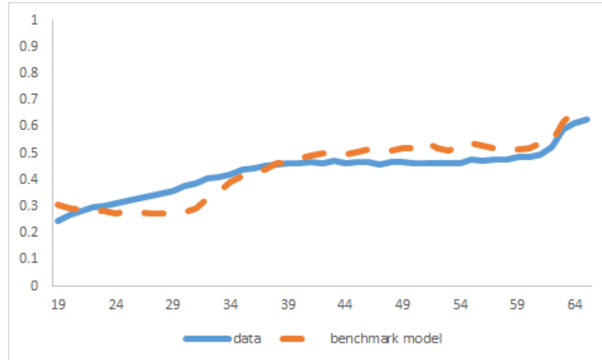
Figure 7: Education enrollment and attainment by age

Table 8: Additional un-targeted moments

Untargeted statistics	data	model
Slope of mean earnings	0.7456	0.8191
Slope of variance of log wage from 18 to 65	0.0058	0.0074



(a) Mean earnings by age



(b) log variance of earnings by age

Figure 8: Mean and variance of earnings

comparison of model fit on the education behavior dimension. This is also the first paper that successfully matches the discontinuous education choice profile.

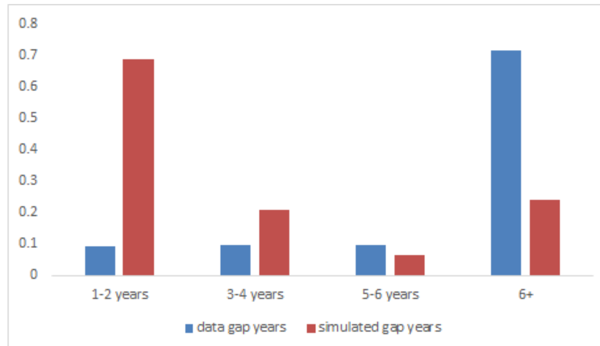
5 Steady state analysis

5.1 Benchmark model qualities

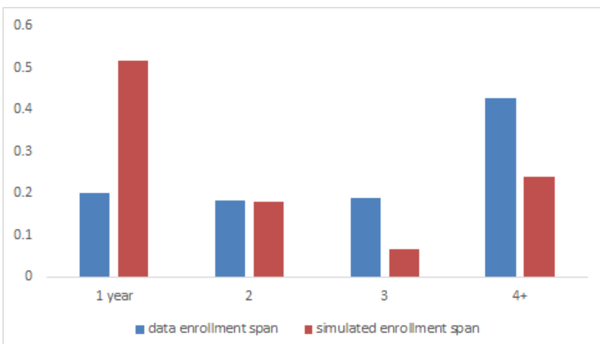
This study is rooted in a broad body of work investigating patterns of earnings dynamics and sources of life-cycle risk and how individuals respond to it.

Guvenen (2007) categorizes two patterns of earnings dynamics from the literature, restricted income process (RIP) and heterogeneous income process (HIP). RIP models argue for the distribution of a persistent income base that expands in a restricted slope throughout the life-cycle across individuals. Though they lack strong empirical support, these models generate good consumption patterns (MaCurdy, 1982; Abowd and Card, 1986; Topel, 1991; Hubbard, Skinner, and Zeldes, 1995; Storesletten et al., 2004). HIP models argue for much less persistence with a distribution of growth pattern across individuals (Lillard and Weiss, 1979; Hause, 1980; Baker, 1997; Haider, 2001; Guvenen, 2007). Despite having better empirical support, HIP models often have difficulties generating the associated patterns of life-cycle inequality, such as consumption inequality (Storesletten, Telmer, and Yaron, 2001). Guvenen

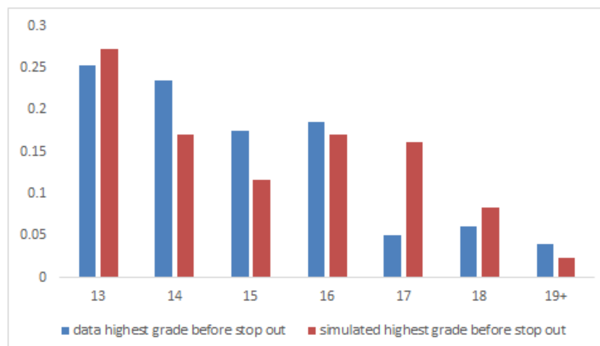
(a) Age returning to school



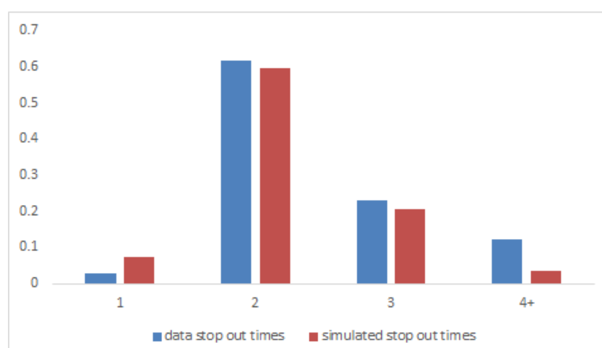
(b) Continuous years not enrolled in school



(c) Continuous years enrolled in school before each dropout



(d) Highest grade completed before dropout



(e) Times repeat dropout and re-enrollment

Figure 9: NLSY79 sample college stopout patterns and model fit

(2007) and Guvenen and Smith Jr (2014) break the link between income and consumption through endogenous learning of one's income process and generate good life-cycle inequality patterns.

I follow both RIP and HIP parameterization procedures and show that the benchmark model generates income processes that fit well in both terms:

$$y^i_{h,t} = g(\theta_t, X^i_{h,t}) + f(\alpha^i, \beta^i, X^i_{h,t}) + z^i_{h,t} + \epsilon^i_{h,t}$$

$$z^i_{h,t} = \rho z^i_{h-1,t-1} + \eta^i_{h,t}, \;\; z^i_{0,t} = 0$$

where $\{i, h, t\}$ describes individual, age, and time; $\{\rho, \sigma^2_\alpha, \sigma^2_\beta, \sigma^2_\eta, \sigma^2_\epsilon, corr_{\alpha\beta}\}$ describe persistence, variances and co-variances of the earnings process. In such a specification, $g(\theta_t, X^i_{h,t})$ describes the common variances across individuals.

Table 9: Statistical models of earnings

	ρ	σ^2_α	σ^2_β	$corr_{\alpha\beta}$	σ^2_η	σ^2_ϵ
RIP model						
Benchmark model	0.981	0.0393	-	-	0.0111	0.0502
Huggett et al. (2011)	0.964	0.283	-	-	0.013	0.025
Guvenen (2009)	0.988	0.058	-	-	0.015	0.061
HIP model						
Benchmark model	0.8239	0.115	0.0003	-0.0041	0.0279	0.0262
Huggett et al. (2011)	0.86	0.264	0.00006	0.0003	0.032	0.006
Guvenen (2009)	0.821	0.022	0.00038	-0.23	0.029	0.047

Following Guvenen (2009), I remove the common variations through fitting a cubed polynomial of age to earnings equation and examine the residual process. $f(\alpha^i, \beta^i, X^i_{h,t})$ describes individual variations, in which α_i is drawn from a distribution governing initial intercept heterogeneity across individuals; β_i describes slope heterogeneity. $z^i_{h,t}$ models the AR(1) process of earnings shocks with persistence ρ and innovation η; $\epsilon^i_{h,t}$ models the transient *iid* shocks across time and individuals. I use minimum distance estimation (MDE) to find parameters of income process. Statistical earnings processes are categorized into HIP (heterogeneous income process) and RIP (restricted income process), with the major difference in RIP removing individual slope differences β (Guvenen, 2009; Guvenen and Smith Jr, 2014). Table 9 compares the benchmark simulated processes to the estimation from Guvenen (2009) and simulation from Huggett et al. (2011) for both HIP and RIP specifications. Across all parameters of the statistical earnings process, the benchmark model shows a strong quality of reflecting the empirical earnings process.

5.2 Insurance value of collegiate education

Section 3.4 lays the theoretical foundation of precautionary motives for accumulating human capital. Attending school largely increases human capital, hence education is used as an insurance device if satisfying Proposition 2. This section documents the strong quantitative support of its quality as an insurance device.

The benchmark earnings shock is $[1.1535, 0.8465]$. The first experiment preserves the mean of the shocks and increases the variance by 1.5 of the original, which becomes $[1.1881, 0.8119]$. The second experiment raises the risk aversion ratio ρ from 2 in the benchmark model to 4.

Table 10: Valuation of collegiate education in variation of risk

		benchmark risk	high risk
Enrollment to Population ratio	benchmark ρ	0.1282	0.1284
	high ρ	0.1345	0.1393
Valuation of school	benchmark ρ	0.0002	0.0001
	high ρ	0.0301	0.0119

Table 10 presents the result. The first two rows report the total enrollment to population ratio. With higher realizations of risk, households with benchmark level ρ increase school enrollment by 0.16% from 0.1282 to 0.1284. At a higher ρ, enrollment increases by 3.4% to 0.1393 from 0.1345 at the benchmark risk level. With a higher risk aversion ratio ρ, more households attend school in each risk category. With the benchmark risk level, doubling ρ raises school enrollment by 5% from 0.1282 to 0.1345, and it raises by 8.5% at the high risk level from 0.1284 to 0.1393. The higher the risk, the higher the likelihood that an individual will enroll in school to prevent the risk, and more risk averse households are more likely to invest in schooling.

The last two rows of Table 10 show the valuation of schooling through utility adjusted consumption. By arbitrarily removing schooling states in the simulation[8], it calculates how much consumption compensation households need in order to achieve the same level of aggregate utility as with schooling. Liu, Mogstad, and Salvanes (2016) refers to it as a measure of "willingness-to-pay" to education. As the realization of risk increases, the valuation of school decreases, from 0.0002 to 0.0001 in benchmark ρ and from 0.0301 to 0.0119 in high ρ, because the realization of a lower ϵ_w permanently reduces the value from learning in school. As risk aversion ρ increases, households value education much more, from 0.0002 to 0.0301 and from 0.0001 to 0.0119 in the benchmark risk level and high risk level respectively.

5.3 Aggregate implications of collegiate education

Under the general equilibrium framework, this study examines the macro implications of collegiate education. Table 11 reports the comparison between the benchmark model and removing all education decisions.

Table 11: Macro implications

Statistics	Benchmark	No school
Y	100	96.53
K	100	102.58
Physical unit of labor	100	97.43
Efficiency unit of labor	100	89.12
r	100	89.36
w	100	102.17
Labor productivity	100	99.07

Removing collegiate education choices reduces interest rate r to 89% of the benchmark

[8]Essentially a partial equilibrium simulation, keeping all prices and stationary equilibrium results intact; it only varies the simulation step by forcing all full time and part time school state to unemployment.

level. Households lose the ability to self-insure and reallocate inter-temporally through the education channel; hence savings become the only way to self-insure. Increasing savings raises capital by 3% and reduces interest rate in a general equilibrium.

To receive a negative ϵ_w shock, households can no longer respond by enrolling in school; instead, they can only choose to withdraw from working into the complete leisure island. In a complete leisure state, human capital depreciates by 2% annually instead of receiving a large negative shock. Therefore, the labor supply decreases, leading to a drop in physical units of labor in the economy to 97% of benchmark level, even though wage rate increases by 2%. Efficiency units of labor drop even further to 89% of the benchmark level, given households lose the lumpy human capital investment opportunity. With a large drop in labor supply, output drops to 96.5% of the benchmark model. Labor productivity, measured by total output over total physical unit of labor, drops accordingly.

5.4 Sources of lifetime earnings inequalities

Though successful, the studies mentioned in 5.1 only find empirical inequality patterns. New directions seek to identify specific sources and the corresponding *ex-ante* self-insure and *ex-post* adjustment channels that generate earnings dynamics (Lise, Meghir, and Robin, 2016; Heathcote, Storesletten, and Violante, 2014; Altonji, Smith, and Vidangos, 2013; Huggett et al., 2011; Heathcote, Storesletten, and Violante, 2010; Low, Meghir, and Pistaferri, 2010; Low and Pistaferri, 2010; Heathcote, Storesletten, and Violante, 2009; Heathcote, 2009; Meghir, 2004; Meghir and Pistaferri, 2011). Depending on sources of risk, households may often self-insure to a certain extent and adjust consumption, labor supply and human capital investment differently *ex-post*. Precautionary savings is a key *ex-ante* response of households facing income uncertainty. Households respond to unemployment risk and matching risk by rejecting or accepting wage offers (Low et al., 2010). Facing productivity shocks, they may choose to change jobs (Postel-Vinay and Turon, 2010). From the perspective of human capital accumulation, studies focus on inter-generational human capital adjustments (Heckman, Lochner, and Taber, 1998; Attanasio, Low, and Sánchez-Marcos, 2008; Ginja et al., 2010). In this study, I identify a lumpy human capital investment method, higher education, as a self-insurance device and its role post negative earnings shock for an individual intra-generational.

Keane and Wolpin (1997) structurally identify factors contributing to long-term differences across individuals, and Huggett et al. (2011) quantify specific sources of lifetime inequality. They both provide strong evidence for the importance of initial human capital, established at an early age, on lifetime inequality and argue that family financial background at early age does not matter much. However, these studies operate in "black box," where lifetime earnings profiles are calibrated by initial exogenous model conditions, and lack of a clear endogenous transmission mechanism of the exogenous conditions. In this study, I not only confirm their conclusions about the importance of human capital established at an early age, but also show a channel through which it evolves to impact lifetime inequality, i.e. through the timing and level of college education.

A major contribution of my model, which features the empirically supported endogenous education channel in transmitting initial difference, is that it allows for a much stronger impact of initial wealth distribution. A household's financial position in at age 18 determines the timing of college attendance, which in turn alters one's earnings post school. Without such a channel, Huggett et al. (2011) conclude that initial wealth distribution contributes only around 5% importance to lifetime earnings inequality, while in my model, it accounts for up to 15% of the lifetime earnings variations. This is under the assumption that households only intensively modify their human capital trajectory through intensively making decisions about on the job training and labor hours, with the only opportunity cost for job training. Hsieh et al. (2013) show that modeling human capital accumulation with only opportunity cost is insufficient and biased. My model demonstrates the importance of initial wealth distribution, which explains over 25% of lifetime earnings inequality, by introducing extensive decision making on human capital accumulation (college education) and taking into account direct cost (as tuition cost and utility cost) and the opportunity cost. Unrestricted education reduces cross-sectional life-time inequality by 20%.

5.4.1 Impact of initial conditions to lifetime earnings inequality

In the benchmark model, households are born with different human capital endowment and wealth endowment at age 18. Huggett et al. (2011) calibrate the initial endowments through matching the life-cycle earnings profile. I directly re-scale the empirical distribution from NLSY79 data to formulate the initial conditions. Table 12 documents the impact of initial conditions on lifetime earnings inequalities [9].

Table 12: Initial condition to lifecycle earnings inequality

Fraction of lifetime earnings variance	Benchmark setting	Model without school
Lower bound initial human capital	0.2948	0.2717
Upper bound initial human capital	0.2823	0.6323
Lower bound of initial wealth (with borrowing)	0.9985	0.9815
Lower bound of initial wealth (without borrowing)	0.8486	0.952
upper bound of initial wealth	0.8902	1.0289

Note: I use the cross-sectional variance for lifetime earnings of the benchmark model and model without school as the numerator for each column. I collapse the initial distributions according to each of the rows to generate counter-factual cross-sectional variances for lifetime earnings as denominators. The fraction of lifetime earnings variances accounted by each row is then as reported.

The first counter-factual experiment collapses the initial human capital distribution to its lower bound. The variance of lifetime earnings drops by about 71% to 29.5% of the benchmark level. Further removing the schooling option, the variance drops to a similar scale at 27.17% level of the model with initial human capital distribution but no school option.

The second set of counter-factual experiments collapses initial human capital distribution to the upper bound of its initial level. Lifetime earnings variation of the benchmark model drops to 28.2%, and models without school drop to 63.2%. In this scenario, initial human

[9] Following the previous literature, such as Huggett et al. (2011), I capture lifetime earnings by directly summing up the earnings one receives in all periods in the lifetime.

capital distribution explains about 71.8% of variations in lifetime earnings in the model with school and 36.8% in the model without school.

The 71% to 72% drop of earnings variances in the benchmark setting falls within the range documented by Huggett et al. (2011) and Keane and Wolpin (1997).

However, the dramatic differences when collapsing to the lower bound and upper bound of the initial human capital distribution in the model without school illustrates the interaction of education decisions and initial human capital positions, as supported by Proposition 2. A detailed examination of this is presented in the following section.

The next set of counter-factual experiments examines the impact of initial wealth. For the model without a schooling option, if I further remove the initial wealth distribution to the lower bound, it doesn't change the lifetime earnings variance by much: 98.2% (or 95.2%) of the level for the model without schooling, with initial distribution and borrowing (without borrowing). By collapsing the initial wealth to the upper bound when there is no school option, inequality raises to 103% of a model without schooling and with initial wealth distribution. This result is also consistent with Huggett et al. (2011). In a model environment without the direct cost of human capital investment, initial wealth does not matter much: only within 3% differences (4.8% if removing borrowing).

However, for the benchmark model with the schooling option, eliminating initial wealth distribution to the lower bound lowers the benchmark inequality by 15% to 84.2% of the benchmark setting variance level if no borrowing is allowed. But the inequality only drops to 99.85% of the benchmark setting if borrowing is allowed, as in the benchmark. By collapsing the initial wealth to the upper bound, inequality is reduced to 89% of the benchmark setting with initial distribution. Initial wealth condition explains from 0.2% to 15% of the lifetime earnings variance. In other words, when one needs to pay to acquire human capital, initial wealth distribution and borrowing constraints have a much larger impact on inequality.

Individuals without enough wealth cannot afford schools. The larger inequality reduction reflected by collapsing initial distribution to the upper bound of initial wealth levels than to the lower bound (without borrowing, especially) demonstrates a more free use of education as an insurance to income shocks *ex-ante*, reducing inequality. But if everyone is constrained to the lower bound of the initial distribution, it exacerbates the inequality from the initial human capital inequality. In this scenario, no one is able to afford school until certain talented individuals accumulate enough wealth; these individuals attend school, albeit at a later age, which extends the lifetime inequality.

In summary, initial human capital distribution matters most in deciding lifetime earnings inequalities. Initial wealth distribution is also crucial when there is a fixed cost in human capital acquisition. Section 5.5 will present more evidence on the interaction of initial conditions and schooling decisions and on the impact of schooling.

5.4.2 Impact of shocks and schooling to lifetime earnings inequality

Human capital production risk (earnings risk) is the main source of uncertainty in this model. Removing ϵ_w, lifetime earnings variance shrinks to 15%, as in Table 13. Removing the unemployment shocks (λ, δ) reduces the lifetime earnings variance to 76.5% of the benchmark variance.

Table 13: Shocks and schooling to lifecycle earnings inequality

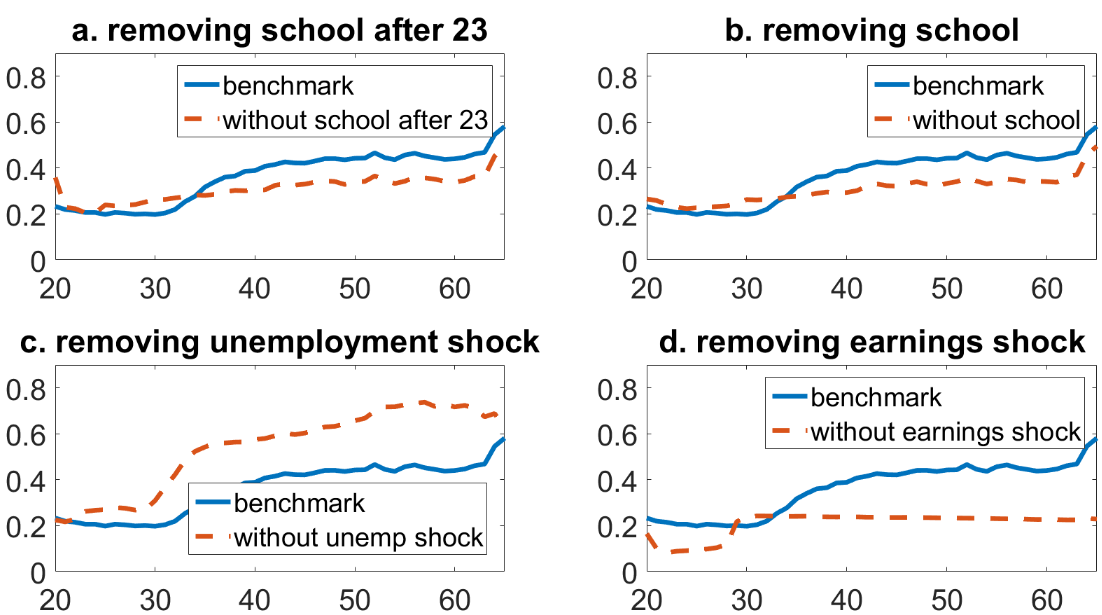
	No unemployment shock	No earnings shock
Fraction of lifetime earnings variance	0.765	0.1529
	Remove schooling	Remove schooling after 23
Fraction of lifetime earnings variance	1.059	1.054

Note: I use the cross-sectional variance for lifetime earnings of the benchmark model as the numerator for all experiments. Each counter-factual according to the column generates a cross-sectional variance for lifetime earnings as each denominator. The fraction of lifetime earnings variances accounted by each column entry is then as reported.

Table 13 also describes the importance of schooling. By shutting down the school channel completely, benchmark earnings variance rises by 6%. Inversely, models that ignore such an extensive endogenous skill upgrading channel impose 6% extra lifetime earnings variance. In addition, when removing the possibility of obtaining education after age 23, as is the traditional consensus, inequality raises by 5%. This demonstrates the importance of college education in inequality reduction, especially for later age education decisions.

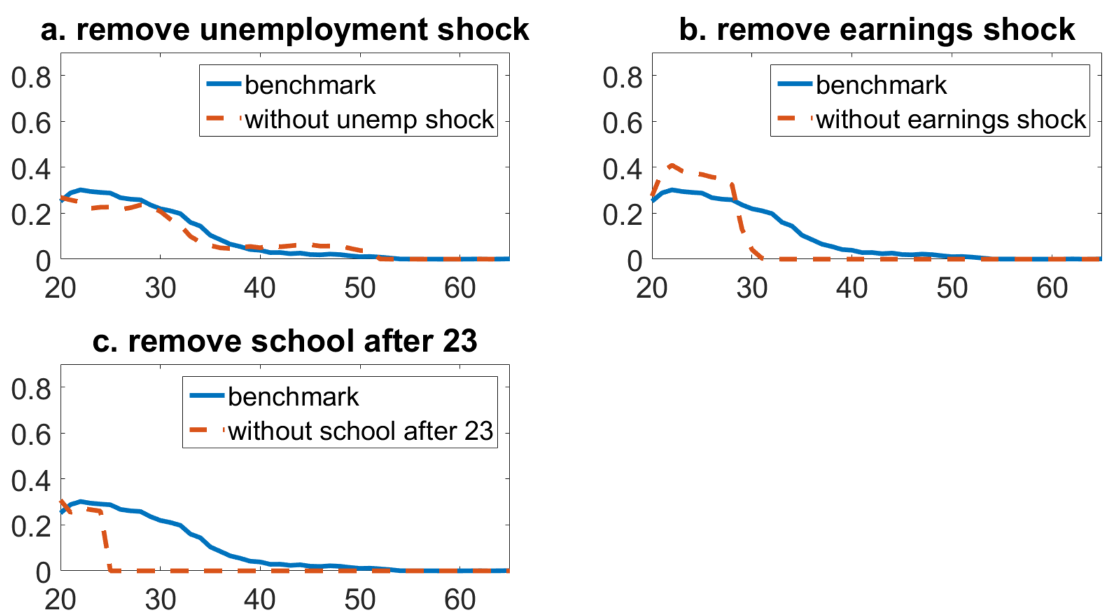
The following figures provide more illustrative evidence of how exogenous shocks impact education decisions and the associated life-cycle earnings inequalities. Figure 10 compares the benchmark model life-cycle earnings inequality trajectory to specifications controlling for shocks and school enrollment. Panel a removes the college education option for all after age 23 and Panel b removes college education completely. Both show similar life-cycle expansion trajectory for earnings volatility. Panel c shows the change after removing unemployment shocks, which roughly preserves the expansion of the earnings volatility over the life-cycle. Panel d removes the earnings shock, except for the initial upward trend of earnings variance, and shows that the earnings volatility completely loses expansion after age 30.

Figure 10: Compare lifecycle earnings inequality by controlling exogenous shocks



The response to shocks in school enrollment is documented in Figure 11. Removing the unemployment shock generates a slightly smaller early age school enrollment and slightly higher later age school enrollment in Panel a; the original benchmark enrollment profile is largely preserved. Removing the earnings shock generates an increasing enrollment in early age and a sharp drop to no more enrollment after age 30 in Panel b. This provides quantitative evidence for Proposition 2, in which without negative shocks, schooling loses its *ex-post* retooling impact to households, hence the enrollment drops to zero after age 30. Knowing no negative shocks to reduce the returns to college education, one would also tend to increase college investment at a younger age. Panel c simply describes enrollment if removing school options after age 23.

Figure 11: Compare enrollment decisions by controlling exogenous shocks



5.5 Impact of school choices on lifecycle inequality and mobility

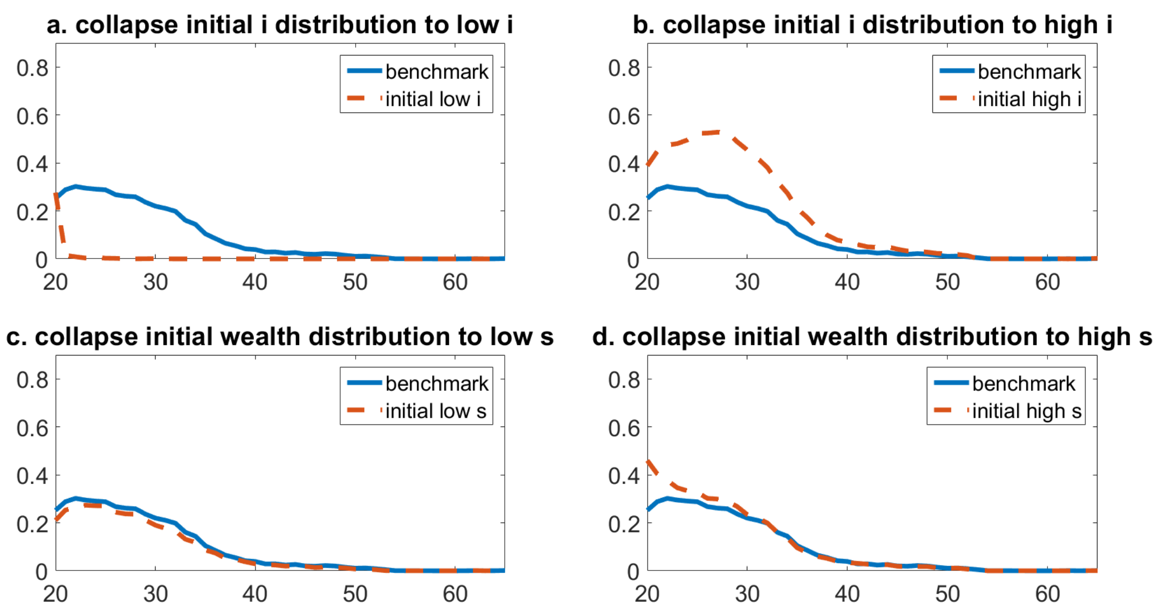
Section 5.4.1 establishes the impact of initial conditions on inequalities and hints at the importance of the transmission channel through college education. This section breaks down the interactions of exogenous conditions and college enrollment decisions and investigates the impact of college education on individuals from a social mobility perspective.

5.5.1 Interactions of exogenous conditions and school choices

Following the experiments conducted in Table 12, Figure 12 reports the life-cycle college enrollment changes, and Figure 13 and Figure 14 document the life-cycle earnings variances.

Figure 12 Panel a shows that with the lowest human capital level, only a very few choose school at the first age. Therefore, with or without school options do not generate a difference in inequality, as in Panel a in Figures 13 and 14. When instead collapsing initial human capital to the upper bound, more individuals choose to attend school at an early age, as in Panel b of Figure 12. This results in a reduction of overall lifetime inequality by 72% as in Table 12, which represents a strong inequality reduction effect.

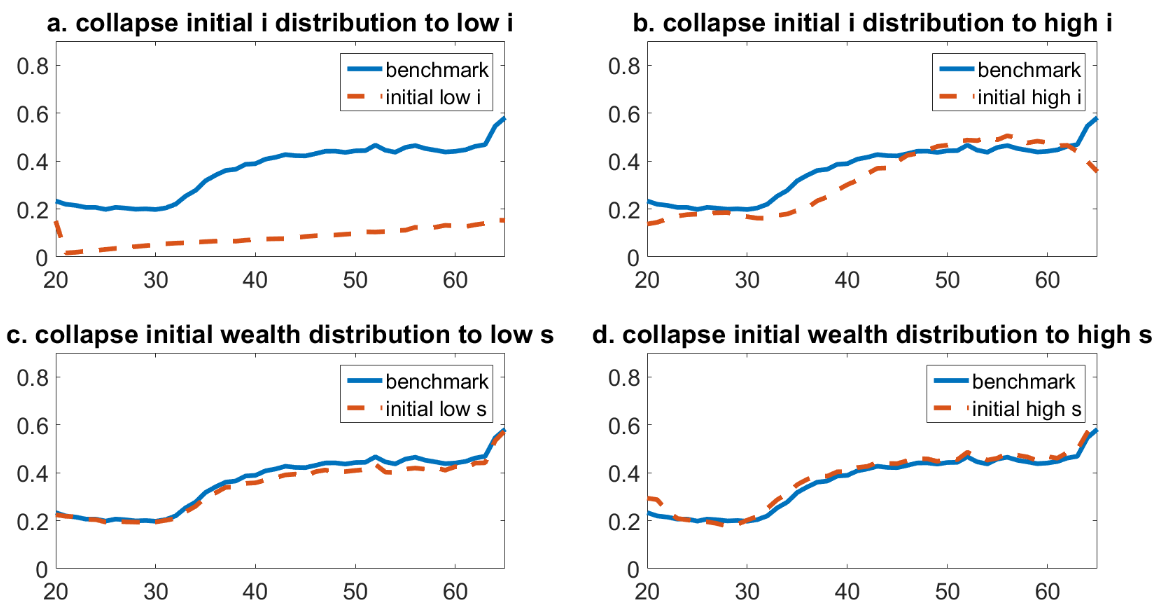
Figure 12: Compare enrollment decisions by controlling initial decisions



These two panels provide evidence for Proposition 2, where threshold of human capital and age determines one's schooling choice. Low current human capital raises $\frac{a\bar{g}e^{p}}{i^{x}}$ and reduces the likelihood of college attendance.

Collapsing initial wealth distribution to the lower bound only slightly reduces early age education decisions, as in Panel c of Figure 12, since households are able to borrow to attend school. Collapsing it to the upper bound shows a more significant increase of initial enrollment from around 0.3 to 0.5 at the first age, as in 12 Panel d.

Figure 13: Lifecycle earnings variations by controlling initial conditions for benchmark model

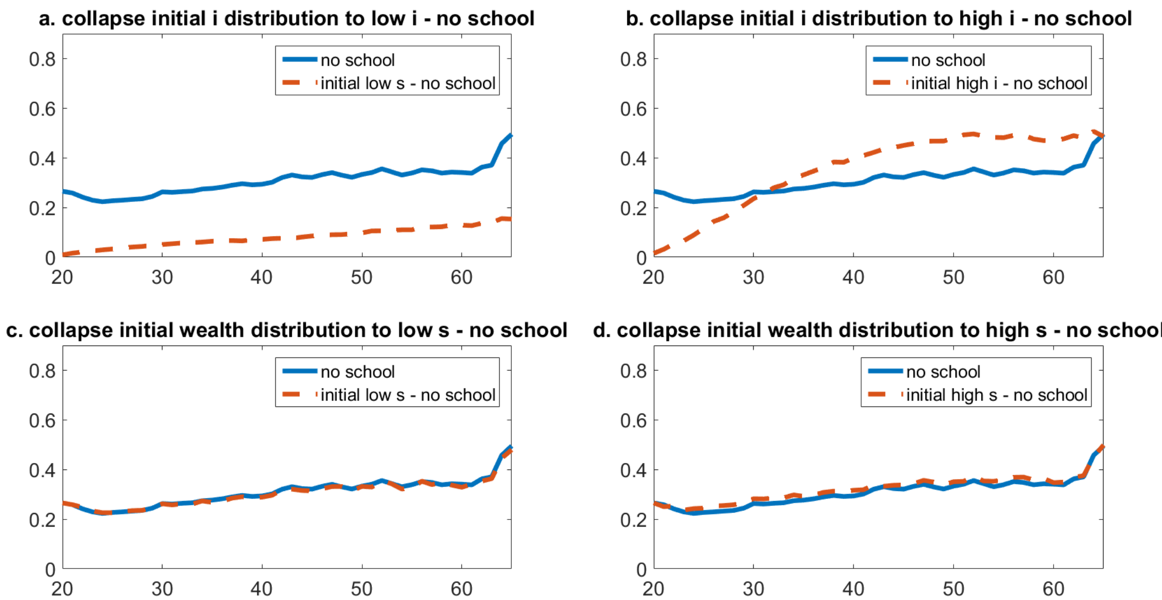


Panel b in Figure 13 collapses to the lower bound of initial human capital and shows a reduction of inequality for almost every age in benchmark model. In Panel b of Figure 14, there is a larger expansion path of inequality when removing the school option. This further provides evidence that schooling reduces inequality.

Panel c and d of Figure 14, which do no include the school option, show that removing the initial wealth distribution doesn't change much to life-cycle earnings inequality. Panel d in Figure 13 shows a slight reduction of inequality in all ages, since collapsing financial wealth to the upper bound allows everyone to afford college. Removing financial constraints to distort education resources provides an inequality reduction effect.

Table 14 presents the difference of college attainment information across individuals with different initial conditions. The higher one's initial human capital, the more likely one is to obtain a BA at an earlier age. Individuals are also more likely to finish their BA by age

Figure 14: Lifecycle earnings variations by controlling initial conditions for no school model



25-30. Initial wealth also matters, with 41% of individuals from the top quintile completing their BA by age 30, compared to 8% of those from the lowest quintile. More individuals from wealthier families tend to complete a BA. Hence, wealth matters through educational choices and their timing, and it impacts the lifetime earnings inequality.

Table 14: Share achieved BA by age and initial conditions

Initial human capital	by 25	25-30	30-35	Total	Initial wealth	by 25	25-30	30-35	Total
1st	0.00	0.00	0.00	0.00	1st	0.00	0.08	0.07	0.16
2nd	0.00	0.00	0.00	0.00	2nd	0.01	0.12	0.09	0.23
3rd	0.01	0.14	0.12	0.28	3rd	0.01	0.25	0.16	0.42
4th	0.02	0.39	0.34	0.78	4th	0.01	0.27	0.21	0.51
5th	0.02	0.51	0.32	0.88	5th	0.02	0.39	0.27	0.71

Figure 15 finds the college completion pattern when controlling for initial wealth or human capital position. Less talented individuals from lower family wealth backgrounds are less likely to obtain a BA. For each human capital quintile, more individuals from higher initial wealth quintiles obtain a BA. This figure shows that initial family wealth hinders efficient allocation of college education resources, despite having the borrowing option in the benchmark model.

5.5.2 Impact of college education and social mobility

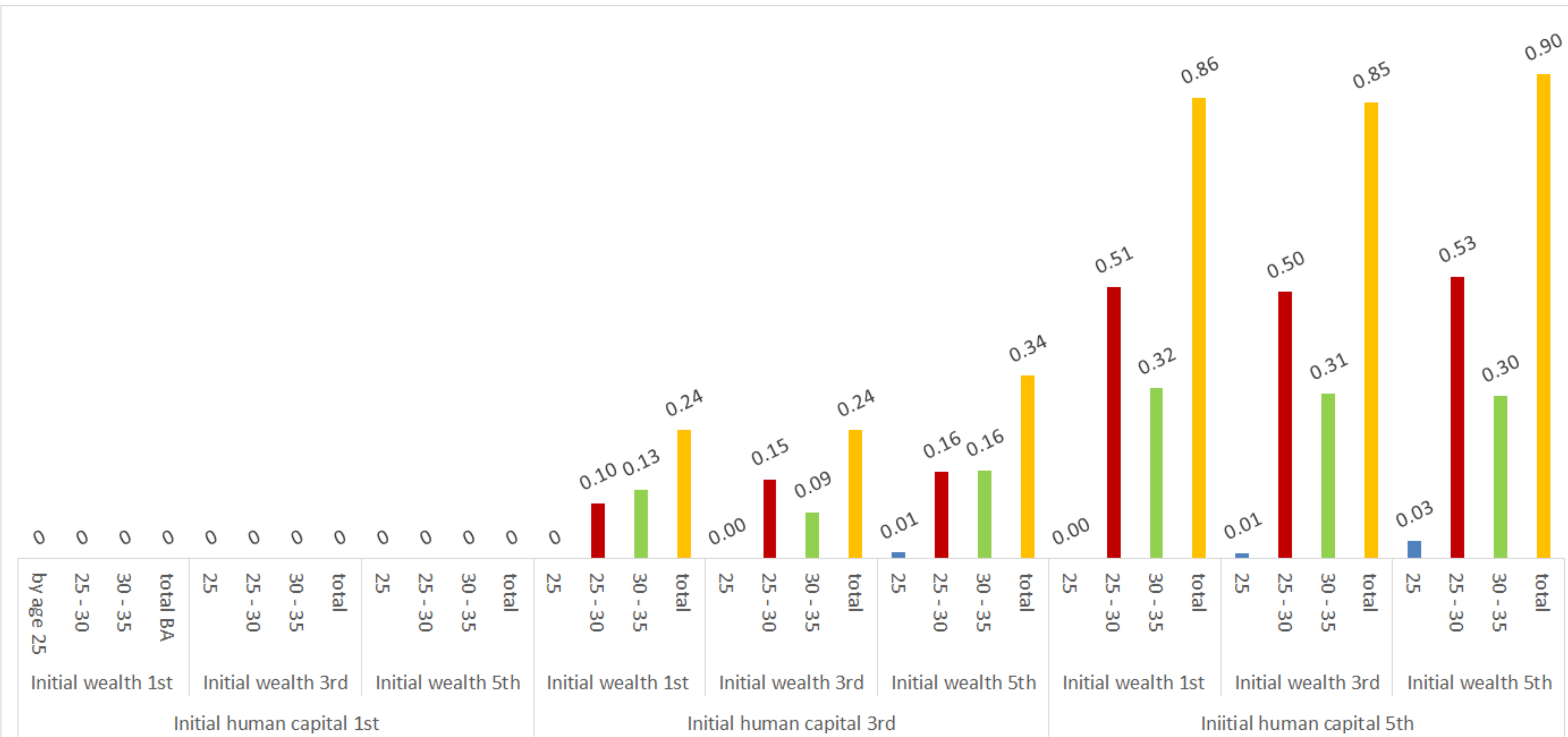
I use two methods to describe the life-cycle social mobility: 1. life-cycle elasticity of income (LCE) and 2. quintile transition matrix. Both methods describe the possibility that one moves from an initial earnings position at age 18 to a lifetime earnings position. LCE is developed following the inter-generational elasticity of income (IGE) method used in Solon (1999) and Chetty et al. (2011). LCE is the β_2 coefficient from the log-log regression:

$$logy_{lifetime} = \beta_1 + \beta_2 logy_{age18} + \epsilon$$

LCE shows that for each one percent increase of initial earnings potential (human capital) at age 18, one's lifetime earnings increase by β_2 percent. The higher LCE, the smaller life-cycle social mobility is. Quintile transition is a straightforward method showing the percentage of individuals from the age 18 earnings potential quintile transitioning to the lifetime earnings quintile. For the rest of the analysis, I simulate the stationary equilibrium for 5000 individuals over their life-cycle for the analysis. For both measures, I examine social mobility from the initial human capital position to the lifetime earnings position and the initial family wealth position to the lifetime earnings position. The transition from initial human capital to lifetime earnings illustrates the approximated life-cycle intra-generational social mobility. Since net family income at age 18 is largely represented by parents' income, the transition from initial wealth position approximates intergenerational social mobility.

Table 15 presents results for LCE. The first row measures the social mobility from initial human capital level to lifetime earnings position measured using LCE; the second row examines the transition from initial wealth level to lifetime earnings. Intra-generational social mobility from the initial human capital position to the lifetime earnings is much more rigid

Figure 15: Share achieved BA by initial conditions



Note: Share of individuals from each category that obtain a BA by age. Categories are defined by controlling for initial human capital quintiles (1st, 3rd, 5th) and for each initial wealth quintile (1st, 3rd, 5th) in the benchmark model (0.512) compared to the model without school (0.369). These observations further support that households use schooling as a means of self-insurance against unemployment and earnings shocks. In the model with no school, under the negative shocks, households can only adjust savings and consumption. They may choose non-working as an insurance against a large negative shock. But in benchmark model, households front load schooling so that they may accumulate larger human capital to insure against future negative shocks. Therefore, in the benchmark model, given initial human capital distribution, households can largely preserve their initial position endogenously; this is less possible in the model without schooling.

Table 15: Life-cycle elasticity earnings income

	Benchmark		No school
for initial human capital	0.512		0.369
for initial wealth	0.343		0.251
	With college degree	Without college degree	
for initial human capital	0.410	0.251	
	Young degree earners	Old degree earners	
for initial human capital	1.131	0.579	

The benchmark model produces an inter-generational social mobility of 0.343, similar to 0.344 reported by Chetty et al. (2011). Without schooling, initial wealth background has a much smaller impact on lifetime earnings (0.251 compared to 0.343 in benchmark model).

Further decomposing the sample, those with college degrees tend to have less social mobility than those without (0.41 vs 0.25) in the benchmark model. This also supports the fact that college education helps self-insure against life-cycle earnings risks.

Young degree earners are those who received their BA by age 25 while old degree earners are those who received their BA between the ages of 25 and 30. Young degree earners have the most rigid social mobility (1.131). They are from the highest initial human capital and upper initial wealth quintiles, as documented in Table 15, and college education largely secures their earnings position over the life-cycle. Those who received their BA at a later age have less social mobility, since they are able to use college education to modify the impact of their initial conditions.

Table 16: Social mobility matrix from initial human capital position to lifetime earnings position

	benchmark social mobility					No school social mobility				
	Lifetime earnings quintile					Lifetime earnings quintile				
Age 18	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
1st	0.482	0.340	0.140	0.037	0.002	0.476	0.290	0.134	0.091	0.010
2nd	0.335	0.365	0.199	0.077	0.024	0.332	0.309	0.199	0.116	0.045
3rd	0.136	0.223	0.324	0.211	0.107	0.126	0.223	0.299	0.218	0.134
4th	0.034	0.077	0.159	0.353	0.377	0.045	0.115	0.191	0.305	0.343
5th	0.011	0.037	0.183	0.322	0.447	0.019	0.091	0.190	0.273	0.427

Table 16 documents the "intra-generational" life-cycle mobility using the quintile transition matrix. The benchmark model tends to have higher diagonal entries than the model without schooling in Table 16. Higher diagonal entries indicate a stronger social rigidity. Individuals are more likely to stay at their initial social location in the benchmark model with schooling for the same reasons that the LCE table illustrated. Most individuals who attended college from Table 15 are from the top human capital quintiles. Accordingly, Table 16 also shows a higher upward mobility for those initially in the 3rd and 4th quintiles.

Table 17: Social mobility matrix from initial wealth position to lifetime earnings position

	benchmark social mobility					No school social mobility				
	Lifetime earnings quintile					Lifetime earnings quintile				
Age 18	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
1st	0.25	0.27	0.18	0.15	0.14	0.25	0.24	0.20	0.17	0.14
2nd	0.23	0.23	0.19	0.18	0.17	0.23	0.21	0.20	0.20	0.17
3rd	0.21	0.20	0.23	0.20	0.17	0.21	0.21	0.21	0.20	0.18
4th	0.20	0.20	0.19	0.21	0.20	0.21	0.19	0.20	0.20	0.21
5th	0.15	0.16	0.20	0.22	0.27	0.15	0.18	0.19	0.22	0.26

Table 17 documents "inter-generational" mobility using the quintile transition matrix. Similarly, the benchmark model tends to have stronger social rigidity as reflected by higher values across the diagonal matrix. In addition, the benchmark model's "inter-generational" social mobility transition matrix resembles the empirical estimation Chetty et al. (2011) documented.

Table 18 compares the sub-samples from the benchmark model simulation between college degree earners and those without a BA. Since only the initial top three quintiles are college degree earners, Table 18 omits the first two quintiles. For all individuals, those with a BA have a much higher upward mobility across the upper diagonal of the matrix and a much smaller downward mobility than those without a BA. This illustrates that for those who can and do complete a BA, their degree can largely move them up the ladder.

Table 18: Social mobility matrix - College subsample

	with BA - social mobility					without BA - social mobility				
	Lifetime earnings quintile					Lifetime earnings quintile				
Age 18	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
3rd	0.007	0.076	0.254	0.420	0.243	0.186	0.280	0.351	0.130	0.054
4th	0.002	0.032	0.152	0.364	0.450	0.150	0.242	0.183	0.314	0.111
5th	0.004	0.019	0.163	0.326	0.489	0.063	0.176	0.333	0.289	0.138

6 Education policy experiment

Studies examining lifetime earnings inequalities are often unable to provide policy evaluations because they lack of endogenous responses to modify the identified exogenous sources of inequality. This paper has a distinct advantage in that it provides policy experiments that could indirectly impact the identified exogenous sources of inequality through altering the transmission channel, college education. In addition to the unconditional implications derived from social mobility in 5.5, two specific education policies are evaluated here: need-based scholarships and merit-based scholarships.

Table 19: Aggregate consequences of education policies

Statistics	Benchmark	Need-based aid	Merit-based aid
Lifetime earnings inequality	100.00	93.85	88.51
Labor productivity	100.00	103.17	101.58
Total enrollment	100.00	108.24	102.75
Scholarship spending		100	152.38

Note: The first four rows are in comparison to benchmark level and the normalize benchmark level to 100. The utility adjusted consumption is conducted by removing the financial aid and reverting to the benchmark setting, which is how much consumption is needed to keep utility the same with financial aid. The report normalizes the merit-based aid level to 100. The scholarship spending is the total tax collected in supporting financial aid. It normalizes need-based aid to 100.

6.1 Need-based financial aid

Need-based financial aid is modeled to offer free tuition to all between the ages of 18 and 22 who are in the lowest quintile of the wealth distribution. In a general equilibrium setting, a simple lump sum tax burdened by all households pays for the financial aid.

The second column in Table 19 presents the aggregate effect of providing need-based aid. Free tuition for the bottom quintile of families increases college enrollment by 8% compared to the benchmark model. It reduces inequality to 93% of the benchmark setting. More individuals going through college training raises overall labor productivity by 3%. Utility adjusted consumption measures how much all households value a tuition-free program for the least wealthy families. When removing this form of financial aid, consumption needs to compensate in order to keep the total utility of the economy the same. It turns out that compared to the utility adjusted consumption for merit-based financial aid programs, households value the impact of need-based much more (over 11740% to the level of merit-based).

In Figure 16, even though going to school is free for all from the lowest initial wealth quintile, the increase of BA achievement for those from the lowest wealth qunitile is very small compared to the benchmark model in Table 15, with a 1 percentage point increase in total. Even though financial aid is awarded only to individuals in the lowest wealth quintile, there is a large increase of BA attainment to those from the higher initial wealth quintiles in general equilibrium.

6.2 Merit-based financial aid

Merit-based financial aid to students mimics the "Texas Top 10 Law" in giving free tuition to the individuals at the highest human capital quintile between the ages of 18 and 22. Financial aid spending comes from a lump sum tax borne by all individuals in the economy as well.

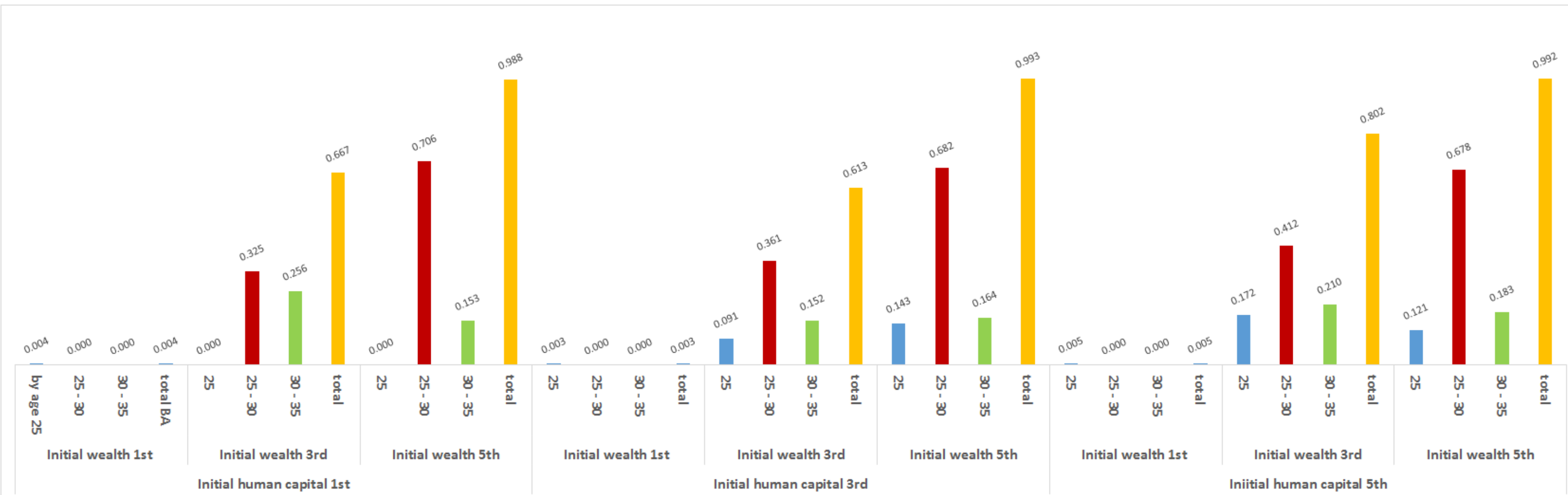
The aggregate implication of merit-based financial aid is recorded in the last column of Table 19. With merit-based financial aid, total enrollment increases by 2.75% compared to the benchmark model, less than with need-based aid. This is because significantly a higher number of top human capital quintile individuals attend schools regardless in benchmark model.

This raises labor productivity by 1.6%, less than with need-based aid as well. It reduces lifetime earnings inequality by 12% to 88.5%, which is much larger than the impact from need-based aid. Figure 17 shows that it significantly raises BA completion for the top human capital quintile individuals. Though it doesn't raise the BA completion for individuals from lower wealth quintiles, it largely raises the BA achievement from the top wealth and human capital quintiles. In addition, the large increase of BA achievement also spreads over to lower human capital quintiles in the general equilibrium. Therefore, it largely reduces inequality.

In addition, because more individuals from the top human capital quintiles choose to attend school, scholarship spending towards these individuals is 52% higher than the scholarship spending towards the lowest wealth quintile individuals.

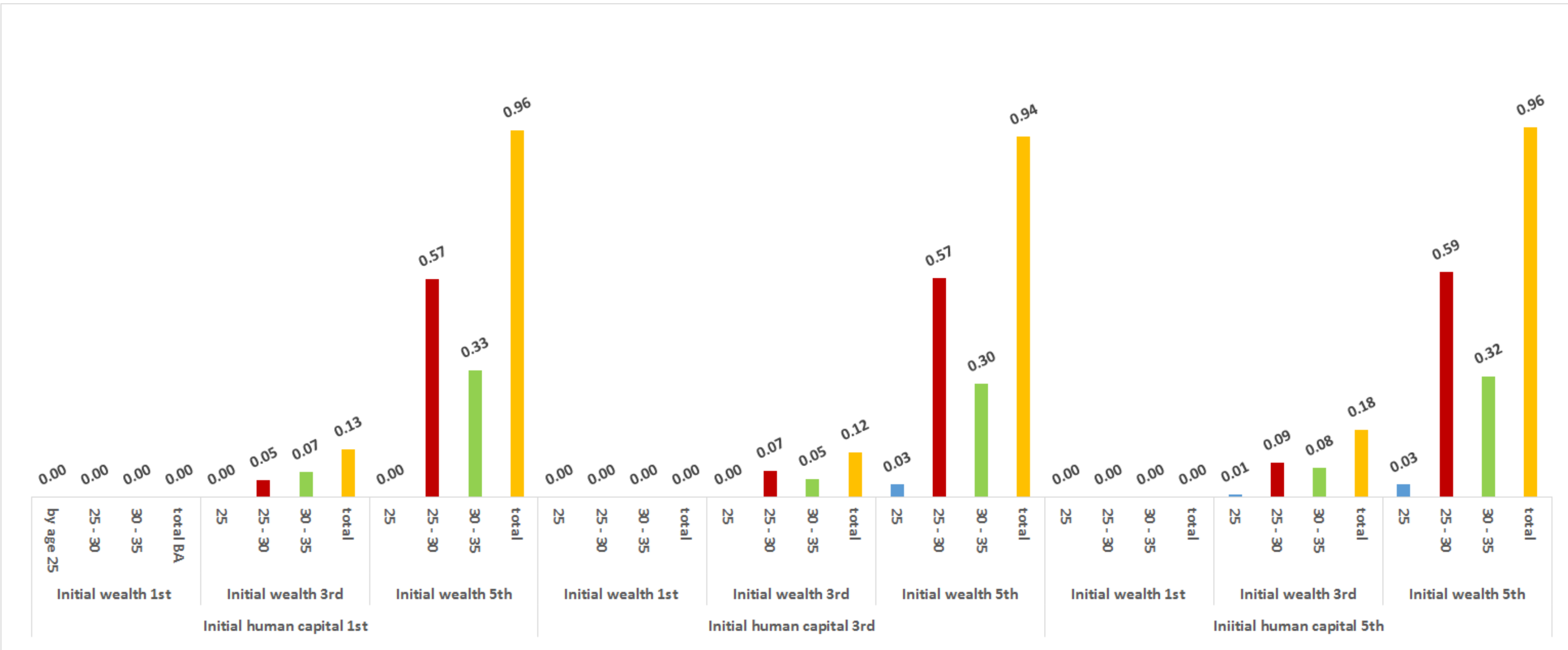
In summary, both financial aid policies encourage college enrollment and inequality reduction. Need-based aid largely increases the social welfare as measured by utility adjusted consumption. Despite being more effective in reducing inequality, merit-based programs are

Figure 16: The impact of need-based financial aid on BA achievement by initial conditions



Note: Share of individuals from each category that obtain a BA by age. Categories are defined by controlling for initial human capital quintiles (1st, 3rd, 5th), and for each initial wealth quintile (1st, 3rd, 5th)

Figure 17: The impact of merit-based financial aid on BA achievement by initial conditions



Note: Share of individuals from each category that obtain a BA by age. Categories are defined by controlling for initial human capital quintiles (1st, 3rd, 5th), and for each initial wealth quintile (1st, 3rd, 5th) more costly.

7 Conclusion

In this study, I argue that an individual's lifetime inequality is profoundly influenced by one's college education decisions. In particular, I show the theoretical support that households attend college at a younger age as an insurance strategy to boost human capital, thereby insuring against future risk; at a later age, households attend school as an *ex-post* response to unfavorable labor market conditions. To quantitatively examine the role of college education in transmitting life-cycle earnings inequalities, I calibrate the model to U.S. panel data and directly use empirical human capital and family wealth distribution to generate important life-cycle earnings and education decisions. Using the calibrated model, I find the quantitative interactions of initial wealth and human capitals to one's college education decisions, and I make an important contribution to the literature by showing the importance of initial wealth distribution to one's lifetime earnings inequalities, which explains 10-15% of lifetime earnings variance. I further demonstrate the importance of education to the aggregate economy and to one's life-cycle social mobility. Having access to education reduces lifetime earnings inequalities by 6% but generates higher social rigidity. But college education also encourages upward social mobility. Given the importance of college education and its interactions with initial conditions, I establish the strong link between the lifetime inequality transmission mechanism through college education and its timing. Policies that impact the completion and timing of college education, therefore, impact the influence of one's initial conditions on lifetime inequalities.

A Proofs

A.1 Proof of Proposition 1

Proof. Fix $\{\epsilon_w, s, i, c, age, yr, e, age, \Upsilon, \tau, \mu\}$, given ϵ_w, $i'_w = \epsilon_w A i^\alpha$, so is $i'_{sch} = \Delta i$, and s'. [10]

Let $P_1 = (1-\delta+\delta\lambda)$, and $P_2 = \delta(1-\lambda)$, the HH's problem becomes:

$$\begin{aligned} V(\phi,\mu) &= max u(c) - disu_w \\ &+\beta(P_1(u(c') - disu_w + \beta(P_1 E_{\epsilon_w} V^w(\phi'',\mu'') \\ &+P_2 E_{\epsilon_w} V^2(\phi'',\mu''))) + P_2 V^2(\phi',\mu')) \\ & s.t. \\ i'_w &= \epsilon_w A i^\alpha \\ c + s' &= (1+r)s + wi(1-\tau) + \Upsilon \end{aligned} \tag{8}$$

Let $i'_w = i'$ if currently $e = w$. Taking the first order derivative w.r.t. i':

$$\begin{aligned} \frac{\partial V(\phi,\mu)}{\partial i'_w} &= \beta(P_1(D_{i'}u(c') + \beta(P_1 D_{i'} E_{\epsilon_w} V^w(\phi'',\mu'') \\ &+P_2 D_{i'} E_{\epsilon_w} V^2(\phi'',\mu''))) + P_2 D_{i'} V^2(\phi',\mu')) \end{aligned} \tag{9}$$

Since $u(c) = c^{1-\gamma}/(1-\gamma)$, using Benveniste-Scheinkman condition:

$$\begin{aligned} D_{i'}u(c') &= c'^{-\gamma} w(1-\tau) \\ &= ((1+r)s' + wi'(1-\tau) + \Upsilon - s'')^{-\gamma} w(1-\tau) \end{aligned} \tag{10}$$

[10]Since ϵ is the only random variable in the model functions, I select $(e = w)$ for the proof. For all other values of e, the proof goes the same way. By the same token, I only prove the case for $V^w > V^{pt}$; if $V^w < V^{pt}$, the proof goes the same way. If one is at V^2, I prove for $V^{sch} > V^{unem}$; for $V^{sch} < V^{unem}$, the proof goes the same way.

$$
\begin{aligned}
D_{i'}E_{\epsilon_w}V^w(\phi'',\mu'') &= \frac{\partial E_{\epsilon_w}V^w(\phi'',\mu'')}{\partial i''}\frac{\partial i''}{\partial i'_w} \\
&= E_{\epsilon_w}c''^{-\gamma}w(1-\tau)\epsilon'_w A\alpha i'^{\alpha-1} \\
&= E_{\epsilon_w}((1+r)s''+w\epsilon'_w i'(1-\tau)+\Upsilon-s''')^{-\gamma}w(1-\tau)\epsilon'_w A\alpha i'^{\alpha-1}
\end{aligned} \tag{11}
$$

$$
\begin{aligned}
D_{i'}E_{\epsilon_w}V^2(\phi'',\mu'') &= \frac{\partial E_{\epsilon_w}V^{sch}(\phi'',\mu'')}{\partial i''}\frac{\partial i''}{\partial i'_w} \\
&= E_{\epsilon_w}(c''^{-\gamma}w(1-\tau)+x\psi_{sch}age''^{p}(i'^{\alpha}\epsilon'_w A)^{-x-1})\epsilon'_w A\alpha i'^{\alpha-1} \\
&= E_{\epsilon_w}(((1+r)s''+w\epsilon'_w i'(1-\tau)+\Upsilon-s''')^{-\gamma}w(1-\tau)+x\psi_{sch}age''^{p}(i'^{\alpha}\epsilon'_w A)^{-x-1})\epsilon'_w A\alpha i'^{\alpha-1}
\end{aligned} \tag{12}
$$

$$
\begin{aligned}
D_{i'}V^2(\phi',\mu') &= \frac{\partial V^{sch}(\phi',\mu')}{\partial i'} \\
&= c'^{-\gamma}w(1-\tau)+x\psi_{sch}age'^{p}i'^{-x-1} \\
&= ((1+r)s'+wi'(1-\tau)+\Upsilon-s'')^{-\gamma}w(1-\tau)+x\psi_{sch}age'^{p}i'^{-x-1}
\end{aligned} \tag{13}
$$

$\frac{\partial V(\phi,\mu)}{\partial i'_w}$ is a summation of Equation 10 - 13 weighted by combinations of scalar β, P_1, P_2. The variance of $\frac{\partial V(\phi,\mu)}{\partial i'_w}$ becomes:

$$
\begin{aligned}
Var(\frac{\partial V(\phi,\mu)}{\partial i'_w}) &= Var(\beta P_1(((1+r)s'+wi'(1-\tau)+\Upsilon-s'')^{-\gamma}w(1-\tau)) \\
&+\beta^2P_1^2(((1+r)s''+w\epsilon'_w i'(1-\tau)+\Upsilon-s''')^{-\gamma}w(1-\tau)\epsilon'_w A\alpha i'^{\alpha-1}) \\
&+\beta^2P_1P_2(((1+r)s''+w\epsilon'_w i'(1-\tau)+\Upsilon-s''')^{-\gamma}w(1-\tau)+x\psi_{sch}age''^{p}(i'^{\alpha}\epsilon'_w A)^{-x-1})\epsilon'_w A\alpha i'^{\alpha-1}) \\
&+\beta P_2(((1+r)s'+wi'(1-\tau)+\Upsilon-s'')^{-\gamma}w(1-\tau)+x\psi_{sch}age'^{p}i'^{-x-1}))
\end{aligned} \tag{14}
$$

Let $M(i')\equiv(1+r)s'+wi'(1-\tau)+\Upsilon-s''$; let $G(i')\equiv(1+r)s''+w\epsilon'_w i'(1-\tau)+\Upsilon-s'''$. Note that both $G()$ and $M()$ are increasing functions of i'.

$$
\begin{aligned}
Var(\frac{\partial V(\phi,\mu)}{\partial i'_w}) = Var(\beta P_1 \frac{w(1-\tau)}{M(i')^{\gamma}}) \\
+\beta^2 P_1^2 \frac{w(1-\tau)\epsilon'_w A\alpha}{G(i')^{\gamma} i'^{1-\alpha}}) \\
+\beta^2 P_1 P_2 \frac{w(1-\tau)\epsilon'_w A\alpha}{G(i')^{\gamma} i'^{1-\alpha}} + \beta^2 P_1 P_2 \frac{x\psi_{sch} age''^{p} \epsilon'_w A\alpha}{(i'\epsilon'_w A)^{x+1} i'^{1-\alpha}} \\
+\beta P_2 \frac{w(1-\tau)}{M(i')^{\alpha}} + \beta P_2 \frac{x\psi_{sch} age'^{p}}{i'^{x+1}}
\end{aligned}
\tag{15}
$$

Since $x, \psi_{sch}, A, \alpha, (1-\tau)$ are all positive for sensible parameter choices, and $\alpha < 1$, for every fractional components of every term in Equation 15, each of the denominators is monotonically increasing on i'. Therefore, $Var(\frac{\partial V(\phi,\mu)}{\partial i'_w})$ is monotonically decreasing in i'. For $i'_1 > i'_2$,

$$
Var(\frac{\partial V(\phi,\mu)}{\partial i'_1}) < Var(\frac{\partial V(\phi,\mu)}{\partial i'_2})
$$

□

A.2 Proof of Proposition 2

Proof. Let:

$$
NB = V^w - V^{sch} \tag{16}
$$

where V^w comes from Equation 2 and V^{sch} comes from Equation 4. Between working and going to school full time, HH will choose school if $NB < 0$ and choose to work otherwise.[11]

[11] I assign tie breaking rule to working if $NB = 0$.

Given functional forms, parameters, and chosen $s, i, c, age, yr, e, age, \Upsilon, \tau, \mu$,

$$\begin{aligned} NB &= u(c) - disu_{ft} \\ &+\beta((1-\delta+\delta\lambda)V(s'_w, i'_w, yr, w, age+1, \mu') \\ &+\delta(1-\lambda)V^2(s'_w, i'_w, yr, w, age+1, \mu')) \\ &-u(c) + disu_{sch} \\ &-\beta(\lambda V(s'_{sch}, i'_{sch}, yr+1, sch, age+1, \mu') \\ &+(1-\lambda)V^2(s'_{sch}, i'_{sch}, yr+1, sch, age+1, \mu')) \end{aligned} \tag{17}$$

Collecting and rearranging terms, one chooses school if:

$$\begin{aligned} &(disu_{sch} - disu_{ft})/\beta < \\ &(\lambda V(s'_{sch}, i'_{sch}) - P_1 V(s'_w, i'_w)) \\ &+((1-\lambda)V^2(s'_{sch}, i'_{sch}) - P_2 V^2(s'_w, i'_w)) \end{aligned} \tag{18}$$

where $P_1 = (1-\delta+\delta\lambda)$, and $P_2 = \delta(1-\lambda)$; $i'_w = \epsilon_w A i^\alpha$ and $i'_{sch} = \Delta i$; $s'_w = (1+r)s + wi(1-\tau) + \Upsilon - c$ and $s'_{sch} = (1+r)s + \Upsilon - c - \kappa$; $disu_{sch} = \psi_s \frac{age^p}{i^x}$ and $disu_w = \psi \frac{1}{1-1/\gamma}$.

Define $RHS = (\lambda V(s'_{sch}, i'_{sch}) - P_1 V(s'_w, i'_w)) + ((1-\lambda)V^2(s'_{sch}, i'_{sch}) - P_2 V^2(s'_w, i'_w))$, and $LHS = (disu_{sch} - disu_{ft})/\beta = (\psi_s \frac{age^p}{i^x} - \psi \frac{1}{1-1/\gamma})/\beta$.

If $LHS > RHS$, then $NB > 0$, and $V^w > V^{sch}$; vice versa.

Since:

$$\begin{aligned} &s'_w - s'_{sch} \\ &= (1+r)s + wi(1-\tau) + \Upsilon - c - ((1+r)s + \Upsilon - c - \kappa) \\ &= wi(1-\tau) + \kappa > 0 \end{aligned} \tag{19}$$

Therefore, $V(s'_w, :) > V(s'_{sch}, :)$, given that the value function is monotonically increasing in s.

Value function is monotonically increasing in i. For i'_w increasing, $V(i'_w, :) > V(i'_{sch}, :)$; and hence, given s'_w and s'_{sch}, $V(i'_{sch}, s'_{sch}, :) - V(i'_w, s'_w, :)$ decreases in i'_w. The same is true for V^2. Rising i'_w monotonically reduces the value of RHS.

As $i'_w \leq 0$, at $i'_w = 0$, $disu_{sch} \to \infty$, V^{sch} and $V^{pt} \to -\infty$. And wage income indexed to i is forever 0; so $V^w = V^{unem} - disu_w$; households will always choose unemployment when $i = 0$.

$$V(i = 0, :) = V^{unem}(i = 0, :) = u(c) + \beta V^{unem}(i' = 0, :') \tag{20}$$

For $i = \iota$ with $\iota > 0$, HHs receive positive wage $w > 0$, positive human capital accumulation, and $disu_{sch} > -\infty$, hence $V(i = \iota, :) > V(i = 0, :)$. This shows that at the lower bound of $i'_w = 0$, $V(i'_{sch}, s'_{sch}) >= V(i'_w = 0, s'_w)$. At the lower bound if i'_w, $R\bar{H}S > 0$.

For fixed $\frac{age^p}{i^x}$, LHS is a scalar:

$$LHS = (\psi_s \frac{age^p}{i^x} - \psi \frac{1}{1 - 1/\gamma})/\beta \tag{21}$$

Let $\frac{\bar{age^p}}{i^x}$ be the threshold value where $L\bar{H}S = R\bar{H}S$. Given the monotonically decreasing quality of RHS in i'_w, and the upper bound of $RHS = R\bar{H}S$ at $i'_w = 0$, if the scalar from age and i, where $LHS > L\bar{H}S$, $LHS > R\bar{H}S$. There is no crossing of RHS and LHS, and $LHS > RHS$ for all i'_w; and $NB > 0$ always, hence HHs always prefer working to schooling. If the scalar from $\frac{age^p}{i^x}$ makes $LHS <= L\bar{H}S = R\bar{H}S$, there is a single crossing between RHS and LHS. Let $\bar{i'_w}$ be the threshold value of i'_w, where $RHS = LHS$. For $i'_w > \bar{i'_w}$, $LHS > RHS$, HHs prefer working to schooling. For $i'_w < \bar{i'_w}$, $LHS < RHS$, HHs choose to go to school over working. When $RHS = LHS$, HHs are indifferent between school and work.

In summary, this shows that given the threshold combination of age and i, if the combination of age and i is large enough, one will always choose to work. Otherwise, there exists threshold $\bar{i'_w}$ where the lower i'_w, the more likely one chooses school.

For part 2 of the Proposition 2, $i'_w = \epsilon_w A i^\alpha$; hence $\exists\ \epsilon_w < \bar{i'_w}/(i^\alpha A)$ that moves $i'_w < \bar{i'_w}$ and vice versa.

$\square$

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