Technology Usage and Life-Cycle Earnings*

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Abstract

This paper studies how technology usage affects earnings growth and earnings inequality over the life-cycle. I first construct an index to measure technology usage at the individual level and investigate its empirical relationship with earnings. However, reduced-form analysis could understate the impact of technology as it cannot capture the interaction with human capital. To address this concern, I then develop a life-cycle model with a college decision, technology choices, human capital investments, and incomplete markets to quantify the relative importance of technology. The model features rich interactions between technology and human capital investment such that workers with high human capital are more likely to work with advanced technologies and vice versa. Counterfactual experiments suggest that technology usage contributes 25% of the growth in mean earnings and 46% of the growth in life-cycle inequality. In particular, the model generates a reinforcement mechanism between human capital and technology usage which amplifies the growth in mean earnings and earnings inequality. Lastly, I evaluate the role of technology usage for policy implications of non-linear taxation. Results show that the distortionary effect of a progressive tax on earnings growth is larger with the presence of technology usage compared to an otherwise standard human capital model due to the reinforcement mechanism.

Keywords: Human Capital, Choice of Technology, Education and Inequality, Taxation

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1 Introduction

There is a large body of literature that studies the effects of information technology (IT) on labor market outcomes but very few papers have explored this question from the life-cycle view.[1] One important margin that arises from the life-cycle perspective is that technology choice is contingent on previous experience: individuals with proficiency in certain technologies might find it easier to learn new ones compared to those less familiar with technology.

In this paper, I investigate the mechanism through which technology usage affects life-cycle earnings and quantify its relative importance. I develop a life-cycle model featuring rich interactions between technology choice and human capital investments. My results suggest that technology usage contributes to 25% of the growth in mean earnings and 46% of the growth in life-cycle inequality. In addition, I find that technology usage provides additional incentives for a college education, which complements the standard human capital view.

The empirical challenge is to measure technology usage at the individual level. To overcome this obstacle, I construct an index *distance to the frontier* to approximate information technology usage using occupations as proxy following Gallipoli and Makridis (2018). This index, which is based on the importance of IT-related knowledge and skills, measures how far the technology used in one specific occupation is behind the most IT-intensive occupation (frontier technology). This index reflects the relative position of a specific occupation in the technology distribution, which progresses over time.

I first present empirical evidence to show a strong positive relationship between technology usage and earnings. I include the technology index in an otherwise standard

[1] Burstein et al. (2019) study how technology affects inequality and Acemoglu and Restrepo (2020) investigate its impact on employment. Hudomiet and Willis (2021) studies the effect of computerization on near-retirement workers.

Mincer regression and the estimated coefficient on the technology index is positive and statistically significant. In particular, one standard deviation increase in technology usage leads to 17% increase in earnings after controlling for observables. Furthermore, I find that the observed variation in technology usage accounts for 38% of the growth in life-cycle earnings inequality.

This reduced-form analysis might underestimate the impact of technology because it fails to capture rich interactions between technology usage and human capital. The reason is that I observe a strong correlation between technology usage and education in the data: there are more college workers in more advanced technologies. So technology could generate effects on earnings through the interplay with human capital investments, which cannot be directly captured by reduced-form estimates.

To quantify the contribution of technology usage on earnings, I develop a life-cycle model with a college decision, technology choices, human capital investments, and incomplete markets. Individuals are heterogeneous in initial human capital and the cost of a college education which determine their college decisions. Agents who go to college will accumulate additional human capital with the cost of forgoing four years of earnings. During the working stage, individuals maximize utility by choosing which technology to work with and making human capital investments. The model then is parameterized to match life-cycle profiles of technology usage and earnings as well as the college attainment rate.

The novelty of the model is to allow for rich interactions between technology and human capital, which are summarized in three mechanisms. The first mechanism is denoted *direct channel*, in which I assume the earnings are the product of human capital and technology level. This assumption explicitly leads to the complementarity between these two terms. The second one is the *switching channel* where technology switching comes at a cost of loss in human capital. This assumption is built on Kambourov and Manovskii (2009a) where they find human capital is occupation-specific and partially transferable.

The last channel is the *catch-up channel*. Since the entire technology distribution is moving forward over time, one needs to learn new knowledge to stay updated with the current technology. I model this cost of learning as the *catch-up cost*, which decreases with human capital. This mechanism is in the spirit of Galor and Moav (2000) where the time required for learning the new technology diminishes with the level of ability. All three mechanisms will be shown to be important in matching technology usage patterns in the data.

Findings I conduct counterfactual experiments to evaluate each channel separately and their aggregate impact on life-cycle earnings. After shutting down all three channels associated with technology usage, the model boils down to a standard risky human capital investments model. I find that the growth in mean earnings decreases by 26 percentage points and the growth in life-cycle inequality drops by 5.6 log points. Furthermore, the college attainment rate decreases by 11.6 percentage points.

The counterfactual experiments provide two key insights about technology usage. First, the growth in mean earnings and earnings inequality is amplified by the interactions between technology and human capital through a reinforcement mechanism. In particular, technology complements human capital through the *direct channel*. Thus, workers in advanced technologies have more incentives to invest in human capital. Meanwhile, the *catch-up channel* lowers the barrier of technology upgrading for people with high human capital so they are more likely to switch to more advanced technologies.

Second, technology usage plays a crucial role in college attainment, which complements the standard human capital view. In particular, individuals benefit from accumulating human capital during their college education, and this, in turn, facilitates technology upgrading in their future careers. When the complementarity between human capital and technology is weakened, the incentive for additional human capital accumulation during college diminishes, leading to a decline in the college attainment rate.

Lastly, technology usage generates different policy implications in terms of progressive taxation. Recent studies have shown that a more progressive tax distorts the incentive of human capital investments and hence lowers earnings growth.[2] My findings show that the distortionary effects are more pronounced when considering the presence of endogenous technology choice, in contrast to standard human capital models. In the baseline model, a progressive tax suppresses not only human capital investments but also technology upgrading, which further dampens human capital accumulation through the reinforcement mechanism. Therefore technology usage amplifies the impact of nonlinear taxation.

Related literature To the best of my knowledge, this is the first paper to study technology usage patterns from the life-cycle perspective. Previous studies on individuals' technology choices only focus on a short period or infinite horizon. For example, Chari and Hopenhayn (1991) study technology adoption for agents that only live two periods, and Kredler (2014) extends their work to infinite-horizon. Jovanovic and Nyarko (1996) propose a theoretical framework to study the trade-off between learning by doing and adopting new technologies. My work applies important modeling elements from the above papers in a life-cycle framework. The model also shares similar intuitions with the literature on technology adoption from the firm's perspective, like Parente (1994) and Greenwood and Yorukoglu (1997). Specifically, the incentive of technology upgrading decreases with age as the benefit can only be enjoyed for a shorter period when the individual (or firm) is older.

My paper broadens the understanding of earnings inequality by unveiling an im-

[2] See Erosa and Koreshkova (2007) and Guvenen et al. (2014) for exmaple.

portant mechanism associated with technology. My paper not only incorporates key features from previous work, such as uninsurable earnings shocks and risky human capital accumulation, but also includes technology choices as another source of inequality over the life-cycle. It is closely related to Huggett et al. (2011), who find that the difference in initial conditions accounts for the bulk of the variation in earnings inequality. My analysis complements their findings by showing the interaction between technology and human capital as an amplifier of earnings growth and life-cycle inequality.

My work is also closely connected to the literature on occupational mobility. Since the technology index is constructed at the occupational level, technology switching can also be understood as occupational switching. In line with the work of Dillon (2018) and Liu (2019), I find that the opportunity of switching technologies helps mitigate negative earnings shocks. However, instead of focusing on earnings risk in detail, I focus on how technology switching affects earnings inequality, like Kambourov and Manovskii (2009b) and Cubas and Silos (2017). In particular, I conduct my analysis in a life-cycle framework and explicitly emphasize the interplay between technology switching and endogenous human capital investments.

The paper is organized as follows. In Section 2, I present empirical evidence on technology usage and its relationship with earnings. In Section 3, I introduce a life-cycle model with endogenous technology and human capital choices. I discuss the parameterization and model's performance in Section 4. In section 5, I conduct counterfactual experiments to understand model mechanisms. Section 6 evaluates a policy experiment of a non-linear tax on labor earnings. Section 7 concludes.

2 Technology Usage and Earnings

This section is devoted to studying technology usage patterns and their direct effects on earnings. I first construct an index to measure technology usage using occupations as the proxy and then investigate technology usage behaviors. I find there is a significant gap in average technology level between college and non-college workers over the life-cycle. Furthermore, the life-cycle profiles of average technology level exhibit a hump-shaped pattern but the magnitude of fluctuation is relatively small.

I also document a strong and positive correlation between technology level and earnings after controlling for observables. This correlation is robust both at the individual level and the occupational level. In addition, the observed dispersion in technology usage can directly account for 4.3 percentage points of overall earnings inequality and 38% of the growth in life-cycle inequality.

2.1 Measurement of technology

The empirical challenge to study technology usage patterns is the lack of a direct measure at the individual level. To overcome this obstacle, I construct an index *distance to the frontier* to approximate technology usage using occupations as the proxy based on Gallipoli and Makridis (2018). The index is based on how intensively people use information technologies in daily work. The rationale behind this measure is inspired by well-documented facts that information technologies can greatly improve productivity at different levels.[3]

This index measures how far one technology (occupation) is behind the frontier technology, i.e., the most advanced technology. Since the frontier technology is evolving over time, this index can be interpreted as the relative position in the moving technology distribution.

I draw detailed information from Occupational Information Network (O*NET) data set on how intensively workers use information technologies. The O*NET is a comprehensive database of worker attributes and job characteristics. The survey interviews

[3] Stiroh (2002) shows that the usage of information technology improves productivity at the industry level. Bloom et al. (2012) shows a similar result at the firm level. Akerman et al. (2015) find that the adoption of broadband internet improves the productivity of skilled workers.

a random sample of workers in each occupation. Interviewees answer questions on a scale from 1 ("not important") to 6 ("extremely important") that measure the importance of some specific knowledge, tasks, or skills. A large literature has used the O*NET database to analyze the labor market outcomes using the task approach (See Autor et al. (2003) and David and Dorn (2013)).

I construct the index *distance to the frontier* by extracting values of characteristics related to IT technology. Specifically, I consider a set of knowledge, tasks, and skills associated with IT technology and sum up the levels of importance (from 1 to 6). After that, I normalize the values of all occupations to the interval $[-1,0]$. The details of the construction are shown in Appendix A.

This index, as implied by its name, describes how far the technology used in one specific occupation is behind the frontier technology. By construction, the occupation that requires the most intensive IT activities is considered to be the frontier technology and its distance to the frontier is 0. Table 1 shows a sample of representative occupations and their distances in each distance quintile. For instance, janitors are the most common occupation in the first distance quintile (bottom of the technology distribution) and computer scientists are the most common occupation in the 5th distance quintile.

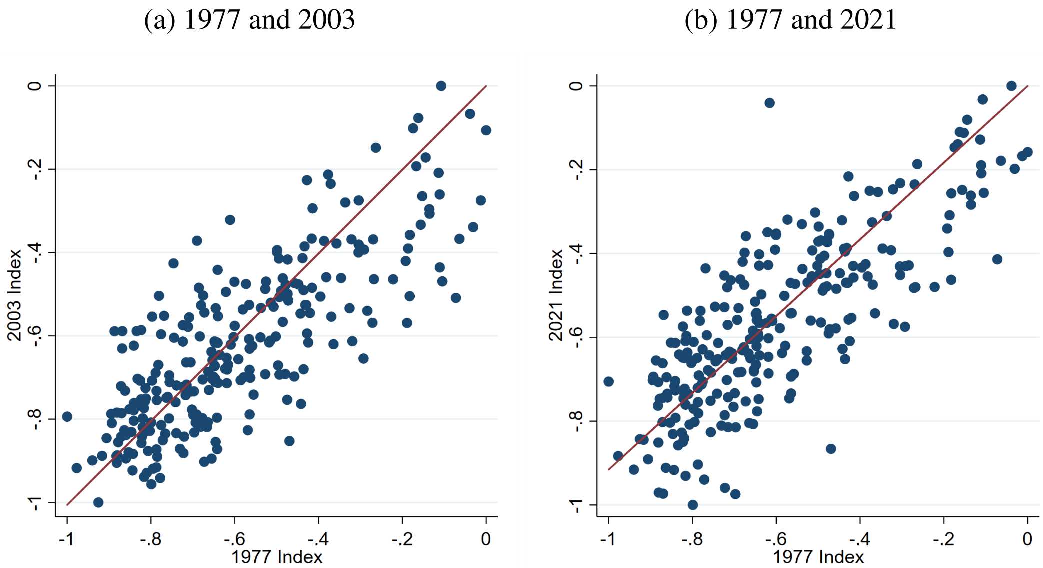
Table 1: Examples of occupation and distance

Distance quintiles	1	2	3	4	5
Occupation	Janitors	Truck drivers	Supervisor of salers	Accountant	Computer scientists
Distances	-0.95	-0.76	-0.57	-0.35	-0.10

Note: The table presents the occupation with the highest employment in each quantile of the distance.

I assume the index is time-invariant over the period of the analysis, i.e. the distance of an occupation relative to the frontier is fixed even though the frontier technology is evolving over time. For instance, consider an occupation with the task of inputting and editing text. Workers used IBM MT/ST, a stand-alone word processing device, in the 1970s and switched to computer software like WordPerfect or Microsoft Word in the

Figure 1: Correlation of Technology Indices over Time



Note: The figure shows the correlation of occupational technology indices across different years.
Source: Author's calculation from the 4th edition of DOT (1977), O*NET 2003 and 2021.

1990s. Since both technologies were up-to-date at their time, the relative distance of this occupation does not change. Meanwhile, the absolute level of technology increased over time because computer software is more efficient than typewriters.

To justify this assumption, I provide empirical evidence to show that there are no significant changes in task intensity and skill composition so this measurement is robust over time. The O*NET data set is only available from 2003 so I use the information from the fourth edition of the Dictionary of Occupational Titles (DOT) conducted in 1977, which is the predecessor of the O*NET, to check how IT-related task intensity changes across time. I construct an index based on a similar combination of skills and tasks for each occupation in the DOT and compare it with the indices from the O*NET in 2003 and 2021 separately.

Standard OLS regressions indicate that the technology index in 1977 has strong explanatory power on the index in 2003 as well as in 2021 with corresponding R-squared of 0.62 and 0.63.[4] Figure 1 also shows the scatter plots of indices between different periods. Though there are some occupations that become more or less IT intensive over time, the above empirical evidence suggests that the skill composition and task intensity from which I infer relative technology level do not change in general.

2.2 Technology usage patterns

Utilizing the constructed index, I document technology usage patterns across education and over the life-cycle. I find a huge variation in technology usage by education: the fraction of college workers increases with technology level. In addition, there is a considerable gap in technology level between college and non-college workers throughout life-cycle. However, the life-cycle technology usage profile is relatively stable as the mean technology level barely changes over the life-cycle for both educational groups. Specifically, the change in the mean distance between age 23 and 60 for non-college workers is 0.04 whereas the gap in average technology level across education is around 0.25.

Data source The analysis draws information from the Current Population Survey (CPS) Annual Social and Economics Supplement (ASEC) over the period 1968-2019. I restrict the sample to full-time full-year male workers with earnings above 50% of the federal minimum wage in that year. Self-employed workers are also excluded.[5] I harmonize occupational codes in both CPS and O*NET to the 2010 SOC code and link the constructed index from the O*NET to the CPS sample.

Technology usage by education The distribution of technology usage varies significantly across educational groups as shown in Figure 2 panel (a). I divide workers

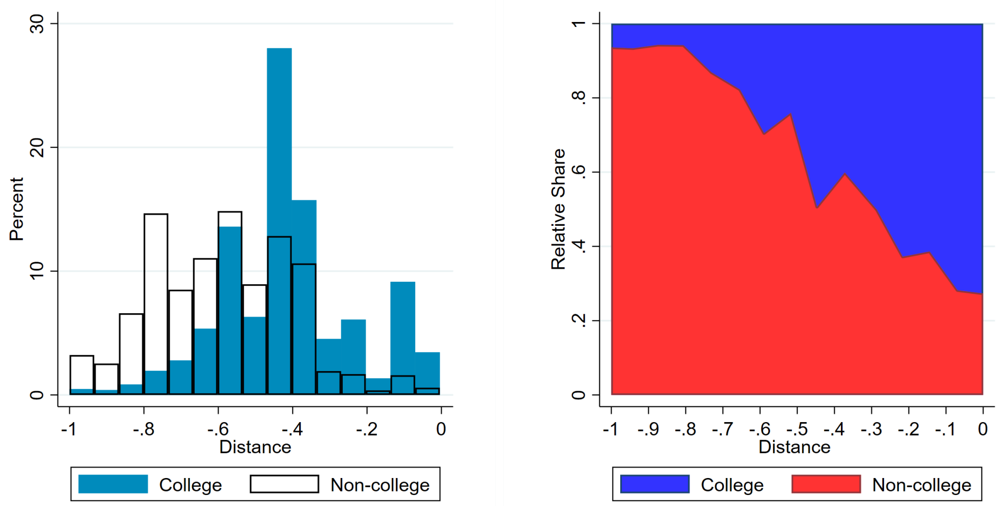
[4]The explanatory power of the index in 2003 on the index in 2021 is even higher, with an R-squared of 0.74.

[5]Similar criteria are applied in the literature on earnings inequality. See Storesletten et al. (2004) and Guvenen (2007) for example.

into two educational groups: with college degrees and without college degrees. College workers are largely concentrated on the right tail of the distribution whereas non-college workers mainly work with less advanced technologies with a distance of less than -0.6.

Figure 2: Technology Distribution by Education

(a) Technology distribution by education (b) Relative Share by education



Note: Panel (a) shows the distribution of technology usage by educational groups: workers with and without college degrees. Panel (b) shows the relative share of college workers and non-college workers by distance (technology level). The technology distribution is divided by 20 bins and the relative share is calculated in each bin.
Source: Author's calculation from CPS ASEC 1968-2019 and O*NET.

Panel (b) shows that the relative share of college workers increases with the technology level. At the bottom of the technology distribution (distance less than -0.8), around 90% of the workers don't have a college degree. For example, the relative share of college workers in janitors (with a distance of -0.95 as shown in Table 1) is around 5%. The share of non-college workers decreases with distance and less than 30% of non-college workers are in the top 10% technologies. The increasing share of college workers suggests there could be a selection mechanism of technology choices based on education.

Life-cycle profiles of technology usage Next, I look at technology usage patterns over the life-cycle. I construct the life-cycle profiles by extracting the age coefficients ($\beta_{i,t}^{\text{age}}$) from the following statistical model:

$$y_{j,c,t} = \beta_j^{\text{age}} + \beta_t^{\text{year}} + \beta_c^{\text{cohort}} + \varepsilon_{c,j,t} \tag{1}$$

where $y_{j,c,t}$ is the statistic of interest from cohort c of age j at time t. Due to the linear relationship between age, year, and cohort ($c = t - j$), it is impossible to identify three terms separately without further assumptions. The common way to deal with this problem is to normalize either the time effects β_t^{year} or the cohort effects β_c^{cohort} to zero and attribute the trend to the other factor.

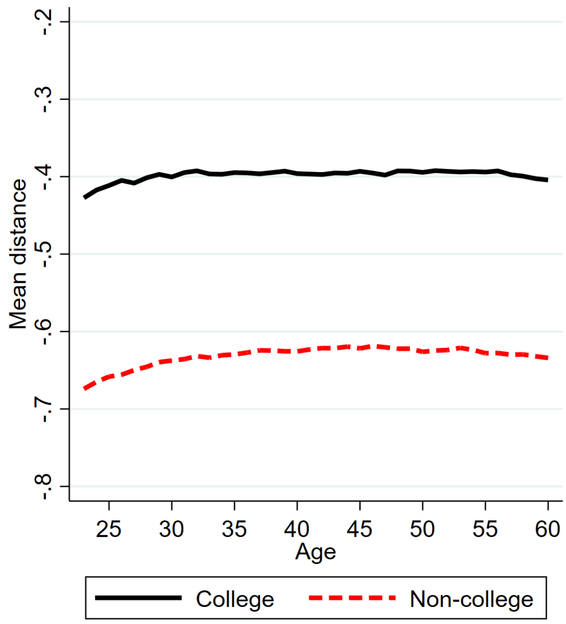
To control for both age effects and cohort effects, I lump three adjacent cohorts into one aggregate cohort which gives me extra degrees of freedom to identify three terms separately.[6] The implicit assumption of this linear statistical model is that the time effects (or cohort effects) only interact with the age profile through the additively separable form.

Two features stand out from the life-cycle profiles of technology usage by education as shown in Figure 3. First, there is a considerable gap in technology level between college and non-college workers even from the beginning of the life-cycle. Specifically, the mean distance of college workers is 0.27 higher than non-college workers at age 25. This difference is 1.3 times the standard deviation of the distance in the entire sample.

Second, the life-cycle profiles of technology usage are relatively flat, especially for college workers. For non-college workers, the growth of mean distance from age 23 to 60 is 0.04, which is equivalent to 20% of the standard deviation of the distance in the sample. The growth of mean distance is only 0.02 for college workers over the same period. Put differently, the gap in technology level across education is relatively constant throughout life-cycle between college and non-college workers.

[6]The shape of age profiles does not change if I only control for year effects or cohort effects.

Figure 3: Life-cycle Technology Usage Profiles



Note: This figure presents the life-cycle profile of technology usage using the constructed index *distance to the frontier* measured at the occupation level. A higher distance means a more advanced technology. Source: Author's calculation from CPS ASEC 1968-2019 and O*NET.

One additional caveat regarding the interpretation of life-cycle profiles: the age profile of mean distance represents the relative speed of technology upgrading since the frontier technology grows over time. By construction, the distance remains constant if one sticks to the same occupation over time, which implies that the worker adopts new technology at a pace that is consistent with the growth rate of the entire technology distribution.

2.3 Technology and earnings

The observation on technology usage patterns naturally begs the question: how does technology affect earnings? I present empirical evidence to show positive correlations between technology level and earnings at different levels, and quantify the contribution of technology to earnings inequality.

To study the relationship between technology usage and earnings at the individual level, I include the technology index to the Mincer regressions as described below:

$$\ln w_{i,t} = \beta_0 + \beta_1 n_{i,t} + \sum_t \beta_{2,t}\text{year}_t + \beta_3 \text{age}_{i,t} + \beta_4 \text{age}^2_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t} \tag{2}$$

where $\ln w_{i,t}$ is log real annual earnings for individual i in year t, $n_{i,t}$ is the distance to the frontier technology constructed at occupational level, and $X_{i,t}$ is the set of control variables, including dummies of race, education, marital status and states.

Table 2: Effects of Technology on Earnings

	Mincer regression			Two-step
	(1)	(2)	(3)	(4)
Technology (β_1)	✗	0.691	✗	0.777
		(0.002)		(0.063)
Occupation dummies	✗	✗	✓	✗
N		1262416		442
R^2	0.326	0.369	0.410	0.473

Note: Column (1) presents the estimation of the standard Mincer regression without the technology index. Column (2) shows the estimation of the modified Mincer regression with the technology index as shown in Equation (2). Column (3) includes broad occupational dummies based on (2). Column (4) shows the results of the two-step regression in Equation (3) and (4) and the R^2 is for the second step regression.
Source: CPS ASEC 1968-2019 and O*NET.

Table 2 column (2) shows that the estimated coefficient on technology is 0.691 with a standard error of 0.002, which is statistically significant from zero. Since the distance takes value from the interval $[-1,0]$, the result implies that workers in the frontier technology ($n = 0$) on average earn 69.1% more relative to workers in the least advanced technology ($n = -1$) after controlling for observables.

The comparison between column 1 and 2 indicates that the inclusion of the technology index increases the R^2 of the standard Mincer regression from 0.326 to 0.369 as shown. This result implies that technology usage contributes 4.3 percentage points of the overall variation in earnings. That is, the technology index increases the explanatory power of the standard Mincer regression by 13%.

Since the technology index is constructed at the occupational level, there is a perfect linear relationship between the technology index and occupation. Therefore one might wonder to what extent the variation is accounted for by the technology index instead of occupational fixed effects. In column (3), I replace the technology index with occupation dummies and find that the R^2 increases to 0.410. Compared to R^2 in the first two columns, it implies that the technology index is able to explain almost half of the variation across occupations.

To solve the collinearity problem, I run a two-step regression which allows me to disentangle the effect of technology usage from occupational fixed effects. I first run the Mincer regression with occupational dummies (OCC_j) as shown in Equation (3). The first stage is to extract the occupational fixed effects λ_j. In the second step, I regress the estimated occupational fixed effects λ_j on the technology index n_j to examine to what extent the variation across occupations can be accounted for by the variation in the technology index.

$$\ln w_{i,t} = \beta_0 + \sum_j \lambda_j OCC_j + \sum_t \beta_{2,t} \text{year}_t + \beta_3 \text{age}_{i,t} + \beta_4 \text{age}^2_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t} \tag{3}$$

$$\hat{\lambda}_j = \beta'_0 + \beta_1 n_j + \varepsilon_j \tag{4}$$

Column (4) in Table 2 shows that the positive relationship between technology and earnings is also robust at the occupation level. The effect of technology even becomes stronger as the estimated coefficient on technology increases to 0.777 with a standard error of 0.063. The reason is that some high-paying occupations like managers or lawyers are not at the top of the technology distribution. Such occupations require interpersonal or leadership skills and do not involve a high intensity of technology usage. As a result, the coefficient on technology will be underestimated if not controlling for such skills.

The two-step regression helps me to disentangle the impact of technology from other valuable skills of an occupation. Therefore its estimation is higher than the one from the modified Mincer regression.

More importantly, as shown in column (4), the R^2 in the second stage of the two-step regression is 0.473. This number implies that almost half of the variation across occupations $(\hat{\lambda})$ can be explained by the constructed index of technology usage. This is also quantitatively consistent with the comparisons in R^2 from column (1) to column (3). Specifically, the occuaptional fixed effects increases R^2 of the standard Mincer regression from 0.326 to 0.410 and the technology index contributes 4.3 percentage points.

Contribution to life-cycle inequality I conduct a simple accounting exercise to demonstrate how technology usage affects life-cycle earnings inequality. I find that the observed variation in technology usage accounts for 38% of the growth in life-cycle earnings inequality.

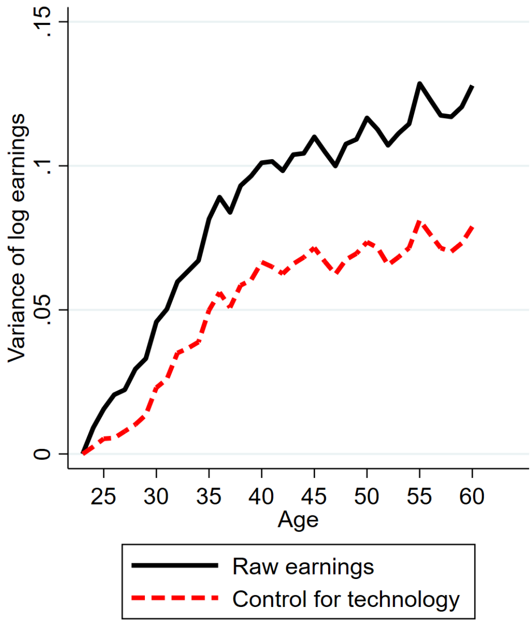
To isolate the impact of technology, I construct an alternative measurement of earnings as described below:

$$\ln \tilde{w}_{i,t} = \ln w_{i,t} - \hat{\beta}_1 n_{i,t} \tag{5}$$

where $w_{i,t}$ is the observed annual labor earnings for individual i at time t, $n_{i,t}$ represents the distance to the frontier and $\hat{\beta}_1$ is the estimated coefficient of the technology index in Table 2 column 2. I denote $\ln \tilde{w}_{i,t}$ as the *residualized earnings*, which rules out the part of earnings that can be explained by technology usage.

I compare the age profiles of life-cycle earnings inequality between the raw earnings $(\ln w_{i,t})$ and the residualized earnings $(\ln \tilde{w}_{i,t})$. In particular, I utilize the statistical model described in Equation (1) and use the variance of log earnings as the metric of inequality. The wedge between these two age profiles of earnings inequality can be understood as the variation accounted for by technology usage.

Figure 4: Life-cycle Earnings Inequality



Note: The figure shows the age profile of variance of log earnings estimated from Equation (1). The solid line represents the raw earnings $\ln w_{i,t}$ and the dotted line represents the residualized earnings $\ln \tilde{w}_{i,t}$ as described in Equation (5), which excludes the part explained by technology. Both levels are normalized to 0 at age 23 for comparison purpose.
Source: Author's calculation from CPS ASEC 1968-2019 and O*NET.

Figure 4 shows that the growth in life-cycle inequality drops significantly using the residualized earnings, which excludes the part explained by technology. Specifically, the level of raw earnings inequality increases 12.5 log points over the life-cycle but the growth decreases to 7.7 log points when using the alternative measurement of earnings. This means that the observed variation in technology usage directly contributes 38% of the growth in life-cycle inequality.

2.4 Taking stock

In this section, I document technology usage patterns over the life-cycle and investigate their empirical relationship with earnings. I find that the usage of IT-intensive technology is positively associated with earnings at both individual and occupational levels. The empirical exercise also shows that the observed dispersion in technology usage could account for 13% of the overall inequality and 38% of the growth in life-cycle inequality.

However, the above reduced-form analysis might underestimate the impact of technology due to the strong correlation between technology usage and education as shown in Figure 2. On one hand, education could affect technology choices. For example, Riddell and Song (2017) find that education increases the probability of technology adoption. On the other hand, educational decisions, or in general, human capital investments, could also be affected by technology usage (Mincer (1989)). Therefore one needs a life-cycle model that can explain the joint distribution of technology usage and education to quantify the relative importance of the interaction between technology usage and human capital.

3 A Life-Cycle Model for Technology Usage

In this section, I develop a life-cycle model with a college decision, endogenous technology choices, human capital investments, and incomplete markets to quantify how technology usage affects life-cycle earnings. The model allows for rich interactions between technology and human capital decisions. I will first ask the model to reproduce technology usage and earnings patterns over the life-cycle for both college and non-college workers and then shut down the technology channel to see what happens to earnings growth and earnings inequality. A tax system is also embedded in the model which allows me to study the role of technology if the economy switches from a proportional tax to a progressive tax.

3.1 Environment

Time is discrete. Each period a unit mass of individuals is born who live up to J periods. The population growth rate is μ. Individuals enter the economy with high-school degrees at age 18. They can spend four years in college or enter the labor market directly. During the working stage, they maximize expected lifetime utility by choosing which technology to work with in each period and making human capital investments. They will retire exogenously after age J_R.

I assume workers supply one unit of labor inelastically in each period. Individuals also borrow and save assets at the risk-free rate r to smooth consumption over the life-cycle. The model abstracts away from the demand side of technologies and takes the growth rate of the technology distribution as exogenous.

Technology and earnings Technology is chosen from the interval $[-1,0]$ to closely follow the concept of the *distance to the frontier* in the empirical part. Earnings is a function of technology n, human capital h, productvity z and time t:

$$w = \exp(z) \cdot h \cdot \gamma^{(\eta \cdot n+t)} \tag{6}$$

where the component $\gamma^{(\eta \cdot n+t)}$ can be interpreted as the marginal productivity of working with technology n at time t.

The parameter γ stands for the growth rate of the technology distribution. If one stays at the same relative position in the technology distribution from t to $t+1$, his earnings would grow at the rate

$$\gamma = \frac{\exp(z) \cdot h \cdot \gamma^{(\eta \cdot n+t+1)}}{\exp(z) \cdot h \cdot \gamma^{(\eta \cdot n+t)}} \tag{7}$$

The parameter η captures the productivity difference within the technology distribution. The earnings ratio between workers in the frontier technology ($n = 0$) and workers in the least advanced technology ($n = -1$) equals γ^η. So η rescales the productivity gap for the interval $[-1, 0]$.

Human capital evolution I model human capital evolution in the spirit of Ben-Porath but the set-up is different mainly in two aspects. First, human capital accumulation is uncertain in the sense that the evolution is stochastic. One's investments can only affect the probabilities. Second, the accumulation process is stepwise such that one cannot skip intermediate levels.

Following Jung and Kuhn (2019), I assume the human capital levels are discrete and represented by an evenly spaced ordered set $[h_{min}, ..., h_{max}]$. During the working stage, individuals make human capital investments by choosing the effort $e \in [0, 1]$ which affects the law of motion of human capital evolution. The cost is captured by the disutility term ζe^2.

The evolution of human capital follows a Markov process with probabilities that depend on the effort e, age j, and education $s \in \{\text{College}, \text{Non-College}\}$. In particular, let h^+ (h^-) denotes the immediate successor (predecessor) of human capital level h, the probability that human capital increases to the next level is given by

$$P_s(h_{t+1} = h^+ | h_t = h, e, j) = \rho^{j-22} \cdot p_s \cdot e \tag{8}$$

where p_s is the baseline probability that varies by education.[7] Human capital depreciation is modeled by the term ρ^{j-22} with $\rho < 1$. When workers get older, it is less likely to climb up the skill ladder as the baseline probability is multiplied by a factor less than

[7] This assumption is to illustrate that the average learning ability is different across education, like in Kong et al. (2018). The detailed discussion is postponed to Section B.2.

one. The probability that human capital decreases to the previous level is

$$P_s(h_{t+1} = h^- | h_t = h, e, j) = (1 - \rho^{j-22} \cdot p_s \cdot e)\alpha_s^{down} \tag{9}$$

where $\alpha_s^{down} \in [0,1]$ and it is also education-specific.

The law of motion of human capital evolution is summarized in the following equation

$$h' = \begin{cases} h^+ & \text{with probability } \rho^{j-22} \cdot p_s \cdot e \\ h & \text{with probability } (1 - \rho^{j-22} \cdot p_s \cdot e)(1 - \alpha_s^{down}) \\ h^- & \text{with probability } (1 - \rho^{j-22} \cdot p_s \cdot e)\alpha_s^{down} \end{cases} \tag{10}$$

When the human capital level is h_{min} (h_{max}), the probability of human capital decrease (increase) is absorbed into the probability of staying.

The human capital accumulation process is stepwise. In order to reach the maximum level h_{max}, one needs to experience all its predecessor levels. If a worker falls from the human capital ladder, it would take some time to climb back to the original level. Put differently, the loss cannot be reimbursed by an excess amount of investments in a short time.

Cost of switching technologies Knowledge accumulated at old technologies cannot be completely applied in new technologies (Chari and Hopenhayn (1991)). I follow Kambourov and Manovskii (2009a) to assume human capital is technology-specific and partially transferable. The following equation shows the amount of human capital that can be transferred when switching to new technologies:

$$\tilde{h}(n, n', h) = \begin{cases} h & \text{if} \quad n \leq n \\ h - (n' - n) \cdot h & \text{if} \quad n' > n \end{cases} \tag{11}$$

Equation (11) shows the switching cost is asymmetric such that it only occurs when people upgrade technology ($n' > n$). If the worker chooses technology downgrading ($n' \leq n$), he can keep the same human capital level after switching. The downward cost is eliminated to decrease the obstacle of technology downgrading, which is a common phenomenon in the data.

The cost of technology upgrading in terms of human capital loss is increasing in the distance of the switch ($n' - n$). This functional form is built on the work from Jovanovic and Nyarko (1996) where they provide micro foundations using the Bayesian updating setup.

More experience can be carried to new technologies if they are highly correlated with the old ones. For example, most of the coding skills in Matlab can be directly applied to Python. However, the experience with Excel, a less-advanced technology relative to Matlab, can hardly be helpful to learn Python. The correlation of technology is interpreted as the distance of the switching ($n' - n$). So the loss in human capital is small if two technologies are closely related.

3.2 College decisions

Workers are endowed with initial human capital h_0 and psychic cost of a college education q. Both initial conditions are drawn from two independent log normal distributions:

$$h_0 \sim LN(\mu_{h_0}, \sigma^2_{h_0}) \quad \text{and} \quad q \sim LN(\mu_q, \sigma^2_q) \tag{12}$$

Given the combination of h_0 and q, workers are endogenously sorted into college path and non-college path. College workers spend four years to acquire the desired human capital level at the cost of disutility which depends on q then they enter the working stage. Another benefit of a college education is that college workers are more likely to work with advanced technologies when entering the labor market relative to non-college workers after graduation. Non-college workers will directly enter the labor market with initial human capital h_0.

Non-college path If the worker does not attend college, he will directly enter the working stage at age 18 with initial human capital h_0. So the value as a non-college (NC) worker is

$$W_{NC}(h_0) = \int_n \int_{z_0} V_{NC}(a_0, h_0, n, z, 18) dF_z(z_0) dF_n^{NC}(n) \tag{13}$$

where $V_{NC}(a_0, h_0, n, z, 18)$ is the value as non-college worker at the working stage with asset level a_0, human capital h_0, technology n, productivity z at age 18. The initial productivity is drawn from the distribution $N(\mu_{z_0}, \sigma_{z_0})$ with CDF $F_z(z)$. Workers's initial technology is also determined stochastically and it is drawn from the distribution $F_n^{NC}(n)$.

College path If the worker decides to go to college, he chooses human capital investment x in the college. The production function of human capital is given by

$$h_c(h_0, x) = (h_0 \cdot x)^{\alpha_h} + h_0 \tag{14}$$

and the cost of investment is captured by the following disutility term

$$q(x + \mathbb{1}\{x > 0\}) \tag{15}$$

This disutility can be understood as the psychic cost of attending college.[8] The worker has to pay (1) the fixed cost of college $q \cdot \mathbb{1}\{x > 0\}$, and (2) the cost that is proportional to the investments $q \cdot x$. Since both terms are increasing in the cost parameter q, it is less costly for people born with lower q to attend college and acquire human capital

[8] See Restuccia and Vandenbroucke (2013) for example.

investments.

The value of a college education is presented as:

$$W_C(h_0,q) = \max_x \quad -q(x+\mathbb{1}\{x>0\}) + \beta^4 \int_n \int_{z_0} V_C(a,h_c(h_0,s),n,z,22)dF_z(z_0)dF_n^C(n) \tag{16}$$

Similarly, V_C stands for the value of a college worker at the working stage. This continuation value is discounted by β^4 since it takes four years to complete a college education. For simplicity, I abstract away from the consumption-saving problem during the college stage.

College workers' initial productivity level is drawn from the same distribution $F_z(z)$ as non-college workers. However, their initial technology choice is drawn from a different distribution $F_n^C(n)$ which has first-order stochastic dominance over $F_n^{NC}(n)$. That is, college workers on average work with more advanced technologies. I postpone the discussion of the details to Section B.1.

College attainment The lifetime value of a worker with initial human capital h_0 and cost q is described as

$$W(h_0,q) = \max\{W_C(h_0,q), W_{NC}(h_0)\} \tag{17}$$

Given the combination of initial conditions, people choose either the college path or the non-college path that generates the highest lifetime value.

The cost of college is to forgo four periods of utility from working stage. The benefit of a college education is mainly two-fold. First, workers can directly make human capital investments in the college stage and it is not subject to the stepwise procedure. That is, one with a very low q could accumulate a lot of human capital during college stage. Second, college workers are more likely to work with advanced technologies relative to high-school workers since they are exposed to new technologies in the college stage. This feature accounts for the difference in the initial technology conditions between the two educational groups.

3.3 Working stage

In this subsection, I describe the value functions in the working stage by education types $m \in \{C, NC\}$. In short, both college and non-college workers face same idiosyncratic productivity shocks over the life-cycle. However, the transitions of shocks and human capital are different by education, which I will emphasize later.

Let $V_s(a,h,n,z,j)$ denote the value of a worker at age j working at technology n with education s, human capital level h, asset level a and productivity shock z at the beginning of the period. The value function is

$$V_s(a,h,n,z,j) = \int \max\{V_s^{stay}(a,h,n,z,j), V_s^{move}(a,h,n,\mathbf{Z},j)\}F(\mathbf{Z}) \tag{18}$$

where $V_s^{stay}(a,h,n,z,j)$ denotes the value of staying at the same relative position and $V_s^{move}(a,h,n,\mathbf{Z},j)$ is the value of moving to new technologies. $\mathbf{Z}$ stands for the vector of technology-specific productivity shocks.

At the beginning of the period, workers first decide whether to stay with the same technology or move to new technologies. The decision is based upon the realization of the vector of shocks $\mathbf{Z}$ over the technology distribution. That is, the worker will know his productivity z_n if he moves to technology n. Each shock z_n is drawn from the same normal distribution $N(\mu_z, \sigma_z^2)$ independently. This vector of shocks only matters when switching to new technologies and does not affect the value of staying.

The value of staying is described below. If the worker chooses to stay, he will work with technology n this period and collect earnings based on current productivity level z and human capital h.[9] After that, the worker chooses the amount of effort e

[9] Here earnings is a function of age j instead of time t. I implicitly assume the baseline cohort enters the labor market at $t = 0$ so the time index conincides with age j.

spent on human capital investments and asset level in the next period a' (or equivalently consumption level c). The taxes are summarized as $T(w,a)$ which I will explain in Section 3.5.

$$
\begin{aligned}
V_s^{stay}(a,h,n,z,j) = \max_{c,a',e} \quad & u(c) - \phi_s(n,h,j) - \zeta e^2 \\
& + \beta \int \sum_{h_{min}}^{h_{max}} V_s(a',h',n,z',j+1) P_s(h'|h,e,j) dF_s(z'|z) \\
\text{s.t.} \quad & a' + c = (1+r)a + w(h,n,z,j) - T(w,a) \\
& a' \geq \underline{a} \quad \text{and} \quad e \in [0,1]
\end{aligned}
\tag{19}
$$

The worker needs to pay a catch-up cost $\phi_s(n,h,j)$ when staying and this cost comes as the disutility term

$$
\phi_s(n,h,j) = \phi_0 (1+n)^{\phi_1} h^{\phi_2} \delta_s^{j-22} \tag{20}
$$

where $\phi_0, \phi_1 > 0$ and $\phi_2 < 0$. Since the entire technology distribution is progressing over time, staying at the same relative position means technology upgrading at the absolute level. Therefore he must update his knowledge to operate the new technology. The catch-up cost is also adjusted by an education-specific discount factor δ_s to model that the learning cost varies over the life-cycle.

The catch-up cost is increasing in the technology level n and decreasing in human capital level h. That is, it is easier to update the latest knowledge for people with higher levels of human capital. This feature captures the spirit of Galor and Moav (2000) where the time required for learning the new technology diminishes with the level of ability. This functional form is also needed to generate the difference in the level of technology between college and non-college workers.

For the continuation value, he will stay at the same relative position n in the next period. His human capital level will evolve stochastically with probability $P_s(h'|h,e)$ as described in Equation (10). This is one distinction between college and non-college workers in the working stage since the baseline probability is different.

Another distinction in the value function across education groups is the law of motion of productivity shock. The shock z evolves stochastically according to a mean-reverting AR(1) process as the following

$$z'(z) = \rho_s^z z + \varepsilon_s^z \tag{21}$$

where $\varepsilon_s^z \sim N(0, \sigma_{\varepsilon_s}^2)$. So the difference comes from the size of innovation $\sigma_{\varepsilon_C}^2$ ($\sigma_{\varepsilon_{NC}}^2$) and the persistence of shocks ρ_C^z (ρ_{NC}^z).

This set-up is common in the literature on income process and earnings inequality.[10] In addition, it serves the purpose of increasing occupational mobility, especially for technology downgrade. One driver behind technology switching in the model is that the worker draws an extremely good productivity shock for one specific technology. In the absence of this process, people would get stuck with technologies where they have high productivity levels. Thus workers will not switch to other technologies unless they draw a better productivity shock, which is less likely to happen since the current shock is already good enough.

The value of switching to a new technology is described below:

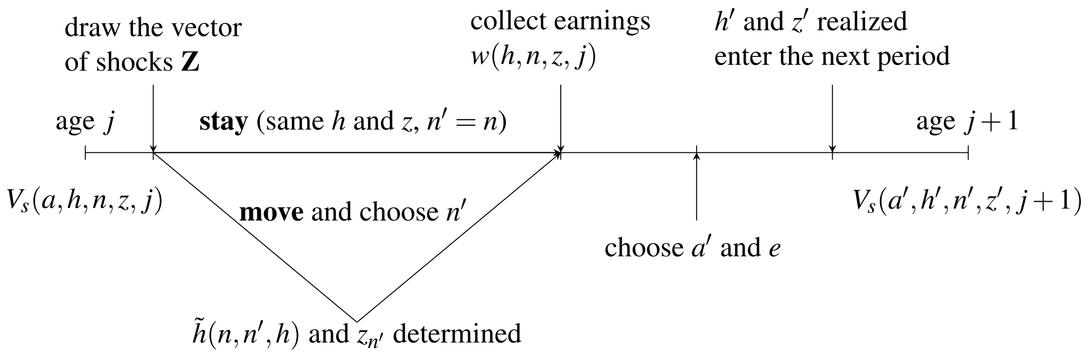
$$V_s^{move}(a, h, n, \mathbf{Z}, j) = \max_{n' \in [-1,0]} V_s^{stay}(a, \tilde{h}(n', n, h), n', z_{n'}, j) \tag{22}$$

where $z_{n'}$ is the technology-specific productivity shock from the vector $\mathbf{Z}$ and $\tilde{h}(n', n, h)$ is the amount of human capital that can be carried to new technology n'. When a worker decides to switch to a new technology n', he will suffer the loss in human capital and then the problem goes back to the "stay" case where he chooses human capital investments and smooths consumption.

The timing of the working stage is summarized in Figure 5. At the beginning of the

[10] See Guvenen (2009) for a empirical investigation in this topic.

Figure 5: Timeline of the working stage



period, workers first draw the vector of shocks **Z** over the technology distribution and then decide to stay or move. If one chooses to stay, he will collect labor income based on current state variables. If he decides to move, he also chooses which technology to work with in this period. Then, his human capital level is determined according to Equation (11) and the productivity level is $z_{n'}$.

After collecting labor income, workers choose effort e to invest in human capital, smooth consumption by choosing asset holding tomorrow a', and then enter the next period. The value function is evaluated after the realization of human capital and shock.

The value function in the last period of working stage is

$$\begin{aligned} V_s^{stay}(a,h,n,z,J_R) &= \max_{a'} \quad u(c) - \phi_s(n,h,J) + \beta V_s^R(a',J_R+1) \\ \text{s.t.} \quad & a'+c = (1+r)a + w(h,n,z,J_R) - T(w,a) \end{aligned} \tag{23}$$

In the last period of the working stage, workers decide how much to save for the retirement period and do not make any human capital investments. The continuation value V_s^R only depends on savings a' and age.

3.4 Retirement stage

Individuals retire after age J_R and get no labor income. They only live off their accumulated assets plus social security benefits net off taxes. The problem of retirement at age $j > J_R$ is described below:

$$\begin{aligned} V_s^{retire}(a,j) &= \max_{a'} u(c) + \beta V_s^{retire}(a', j+1) \\ \text{s.t.} \quad a' + c &= (1+r)a - T(0,a) + b_s^{ss} \end{aligned} \tag{24}$$

Notice that workers in the retirement stage no longer receive labor earnings so the first argument in the tax function is zero. Workers also receive social security benefits after retirement. The benefit is also education-specific and on average college graduates receives more benefit than high-school graduates: $b_C^{ss} = \kappa b_{NC}^{ss}$ with $\kappa > 1$.

3.5 Tax system

The tax system $T(w,a)$ in the model consists of two parts: income tax T^{inc} and social security T^{ss}. Individuals' labor earnings and capital income are taxed at a flat rate τ and the social security system taxes labor earnings at the rate τ_{ss} for individuals at the working stage. So the tax function can be presented as

$$T(w,a) = \tau(w + ra) + \tau_{ss} w \tag{25}$$

After retirement, agents receive fixed social security benefits b_C^{ss} or b_{NC}^{ss} in each period. The social security system is pay-as-you-go, i.e., it finances the benefits from taxes collected from individuals during the working stage. Government also consumes G for non-productive purposes to balance the budget.

3.6 Sources of life-cycle inequality

The sources of earnings inequality over the life-cycle mainly come from three aspects: human capital h, technology n, and productivity shocks z. In this subsection, I discuss these three sources and their associated mechanisms and explain how they affect earnings inequality over the life-cycle.

3.6.1 Interaction between technology and human capital

Technology interacts with human capital mainly in three channels. The first channel is the *direct channel*, i.e., earnings is a function of technology and human capital as shown in Equation (6). This set-up explicitly assumes that technology and human capital are complements. As a result, the marginal benefit of human capital investments increases with technology so people in advanced technologies have more incentives to accumulate human capital. This idea dates back to the insight of Schultz (1975) where technological progress complements ability in the formation of human capital. What's more, the incentive of technology upgrading also varies by human capital due to the complementarity.

The *catch-up channel* indicates that the cost of technology usage negatively depends on the level of human capital as described in Equation (20). This equation indicates it is easier to stay with advanced technologies for workers with high human capital. Since this cost applies to all workers regardless of switching or not, it also imposes barriers to technology upgrading. To sum up, this catch-up channel lowers the cost of technology usage for people with high human capital.

The last channel is the *switching channel* where the technology upgrading comes with the loss of human capital. Since the switching cost is proportional as shown in Equation (11), workers with high levels of human capital will suffer more human capital when switching to better technologies. Thus they are less likely to make a huge step toward frontier technology. This channel works in the opposite direction as the catch-up channel since it discourages people with high human capital to upgrade technology.

The first two channels generate a positive correlation between human capital and technology which amplifies earnings dispersion over the life-cycle. On one hand, the direct channel provides more incentives for human capital investments for workers in advanced technologies. On the other hand, workers with high levels of human capital are more likely to switch to advanced technologies due to the catch-up channel. Consequently, this reinforcement mechanism between human capital and technology will magnify the dispersion in earnings through the interaction between these two components and the correlation will become stronger over the life-cycle. Meanwhile, the switching channel reduces earnings dispersion as it depresses technology upgrading, especially for people with high human capital.

3.6.2 Idiosyncratic shocks

Another important source of inequality comes from idiosyncratic productivity shock z. I follow the standard set-up in the literature to model income risks as an AR(1) process. However, the introduction of technology decisions alleviates the dispersion brought by the shocks. The reason is that the opportunity of switching technologies in each period helps workers mitigate bad shocks, which is in the spirit of work from Dillon (2018) and Liu (2019).

In the standard AR(1) income process, one might experience a sequence of persistent negative shocks because of bad luck. In my model, due to the presence of technology decisions, one can easily "reset" his productivity level by switching to another technology with high productivity shock so the above scenario will not happen. That is, the opportunity of switching technologies makes shocks less persistent, which lowers the level of dispersion generated by productivity shocks.

4 Parameterization and the Benchmark Economy

This section describes how I set the parameters in the model and discusses the properties of the benchmark economy. The parameters are chosen to match (1) the fraction of college workers, (2) life-cycle profiles of mean earnings and variance of log earnings for both college and non-college workers, and (3) life-cycle profiles of mean technology level for both educational groups. I only focus discuss parameters associated with technology usage, which is the focus of this paper. The rest of the parameterization is standard and relegated to Appendix B.

Earnings function The Mincer regression with the technology index is used to identify parameters in the earnings function. Taking log of the earnings function in Equation (6) generates

$$\ln w \quad = z + \ln h + (\ln \gamma\eta) \cdot n + \ln \gamma \cdot t \tag{26}$$

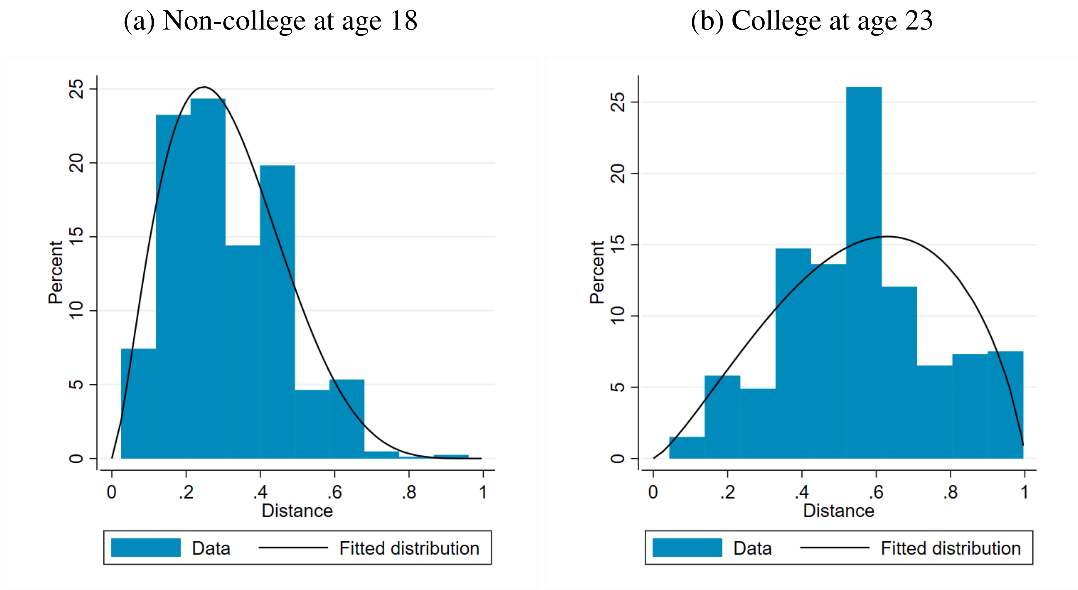
where n is the distance to the frontier and t represents year. Notice that this is analogous to Mincer regression used in the empirical analysis.

Equation (26) implies that $\ln\gamma$ corresponds to the coefficient of year in the Mincer regression and $\ln\gamma\cdot\eta$ maps to the coefficient of the technology index. Since I use year dummies in the Mincer regression, I further run a linear regression on the estimated year dummies and estimate the annual growth rate of the technology distribution is 0.5%, i.e., $\gamma = 1.005$. That is, if one stays with the same technology over time, all else equal, the natural growth rate of his earnings is 0.5%.

After pinning down γ, the parameter η is identified to match the coefficient of the technology index in the Mincer regression. Setting $\eta = 111$ means that the earnings gap between the most advanced technology $(n = 0)$ and the least advanced technology $(n = -1)$ is 0.77 in the model, which is consistent with the empirical findings in Section

2.

Figure 6: Initial Technology Distributions (college and non-college)



Note: This figure shows the initial distribution in terms of the distance for college and non-college workers. The solid lines represent the fitted Beta distribution used for the model as $F_n^{NC}(n)$ and $F_n^C(n)$. Source: Author's calculation from ASEC 1968-2019 and O*NET.

Initial distributions of technology I take the initial technology distributions $F_n^{NC}(n)$ and $F_n^C(n)$ as exogenous and infer them directly from the data. Specifically, I fit the technology distribution at age 18 (23) with the Beta distribution for non-college (college) workers. The advantage of Beta distribution is that it has limited support $[0,1]$. After rescaling, it can be mapped to the interval of technology index $[-1,0]$. Figure 6 shows the fitted distributions and the raw distributions from the data.

Catch-up cost The catch-up cost is the disutility term associated with technology usage, which imposes the barrier that stops workers from upgrading to frontier technology. In particular, ϕ_0 determines the overall level of technology usage and ϕ_1 affects the speed of technology upgrading, i.e. the slope of technology profiles.

The parameter ϕ_2 is the key to generate the technology usage gap between college and non-college workers since the average human capital level is different across education groups. The calibrated value of ϕ_2 is negative, which implies that the catch-up cost is relatively small for workers with more human capital. Thus college workers on average have a higher technology level.

The education-specific discount factors δ_s are important to control for the trajectory near the end of the life-cycle. The catch-up cost will drastically dominate the benefits of technology upgrading as workers become old. Therefore this disutility term is also adjusted by age to generate minor declines in technology level near the end of the life-cycle.

4.1 Understanding technology switching

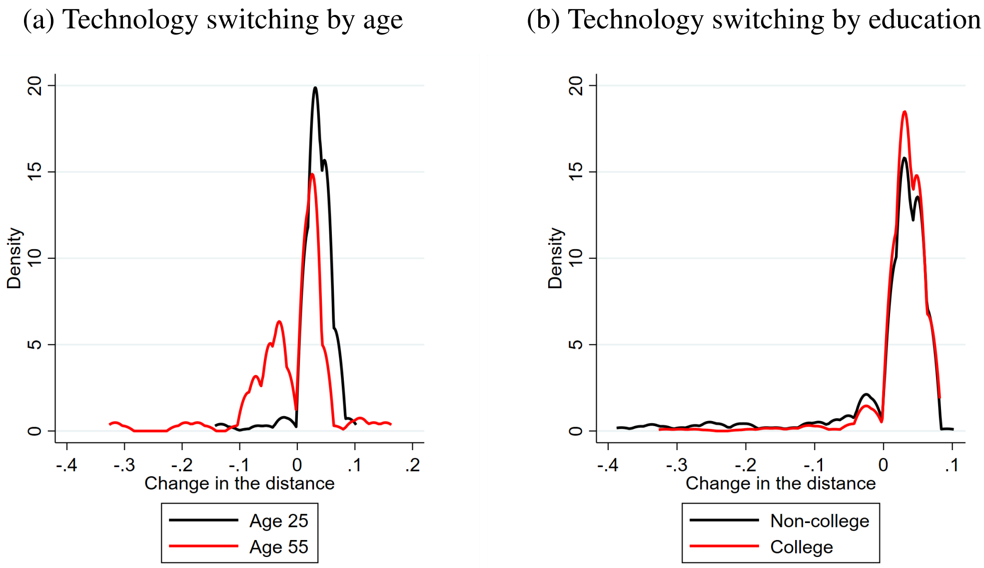
Before showing the model's performance, I first discuss the mechanism of technology switching and how it varies by education and age. In Figure 7, I present kernel density estimation of switching probabilities conditional on workers who switch to other technologies from the simulated economy. For illustration purposes, I only focus on workers in the 3rd quintile group of the distance ($-0.63 < n < -0.53$).[11]

In general, technology switching is asymmetric such that the distribution is left-skewed, i.e., people are more likely to upgrade technology. The reason is that technology upgrade directly delivers a higher utility as it increases earnings and hence consumption. However, the magnitude of upgrade is smaller compared to downgrades. Figure 7 panel (a) shows that young workers are more likely to upgrade technology compared to old workers. Panel (b) conveys a similar message between college workers and non-college workers but the difference is relatively small.

To better understand the distribution of technology switching, I investigate the key

[11]Though technology switching largely depends on the current technology level, the intuition on switching can also be applied to other quintile groups.

Figure 7: Kernel Density of Switching



Note: The figures show kernel density estimations of switching probabilities conditional on workers who are in the 3rd quintile group of the distance in the previous period and decide to switch to other technologies. A positive change in distance implies technology upgrading. Panel (a) shows the density for all workers by age. Panel (b) shows the density for workers at age 25 by education.

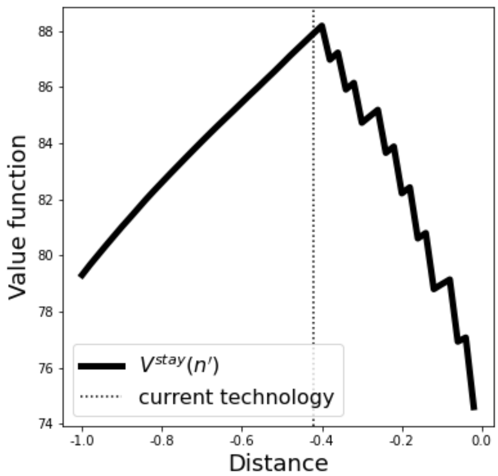
equation:

$$V_s^{move}(a,h,n,\mathbf{Z},j) = \max_{n' \in [-1,0]} V_s^{stay}(a,\tilde{h}(n',n,h),n',z_{n'},j) \tag{27}$$

This equation determines how far a worker would like to switch (n') given the vector of productivity shocks $\mathbf{Z}$. In Figure 8, I plot $V_s^{stay}(a,\tilde{h}(n',n,h),n',z_{n'},j)$ as a function of n' and hold productivity shocks $z_{n'}$ constant for all $n' \in [-1,0]$ for comparison purpose.

The value function is hump-shaped in n'. The value first increases with n' since technology level is positively correlated with earnings. However, two downward forces stop workers from upgrading. First, technology upgrade leads to the loss in human capital that is proportional to the distance of switching $n' - n$ as shown in Equation (11). In addition, workers have to pay the catch-up cost $\phi_s(n',h',j)$ in the new technology n'. Moreover, since they suffer human capital loss, it also exacerbates the catch-up cost as it decreases with h'. These two channels together explain why the value function

Figure 8: Value function $V^{stay}(n')$



Note: The figure shows $V_C^{stay}(a, \tilde{h}(n', n, h), n', z_{n'}, j)$ as a function of n' at age 25 with all state variables evaluated at the median level. I also hold productivity shocks constant for all technologies. The vertical line stands for current technology position n.

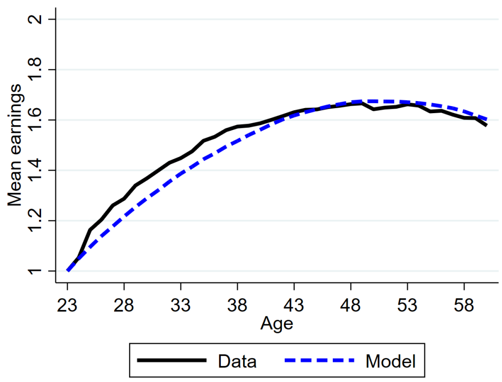
decreases with n' above a certain threshold level. Therefore we see workers prefer a short step of technology upgrade over a long step in Figure 7. The actual switching behaviors are more complicated because shocks vary across technologies. One may switch to a lower-ranked technology because he draws an extremely good shock z for that technology.

4.2 The benchmark economy

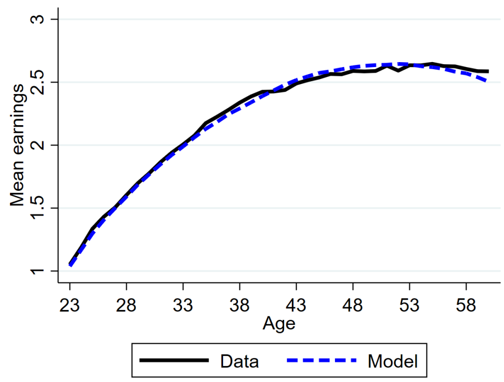
In this subsection, I examine the quantitative properties of the benchmark economy and compare them with the data counterparts. The parameterized model is able to match targeted life-cycle profiles of earnings and technology usage for both educational groups. In addition, the college attainment rate generated by the model is 29.8%, which is quite close to the average college attainment rate (29.4%) over the period 1968-2019 in the CPS sample.

Figure 9: Life-cycle Earnings Profiles

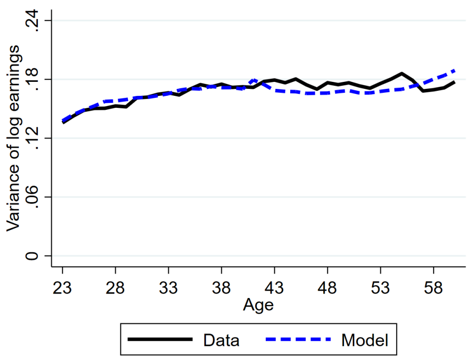
(a) Mean earnings: Non-college



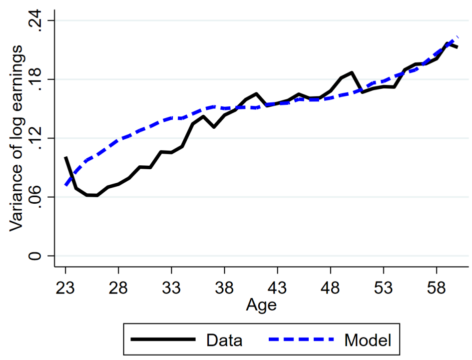
(b) Mean earnings: College



(c) Earnings inequality: Non-college



(d) Earnings inequality: College

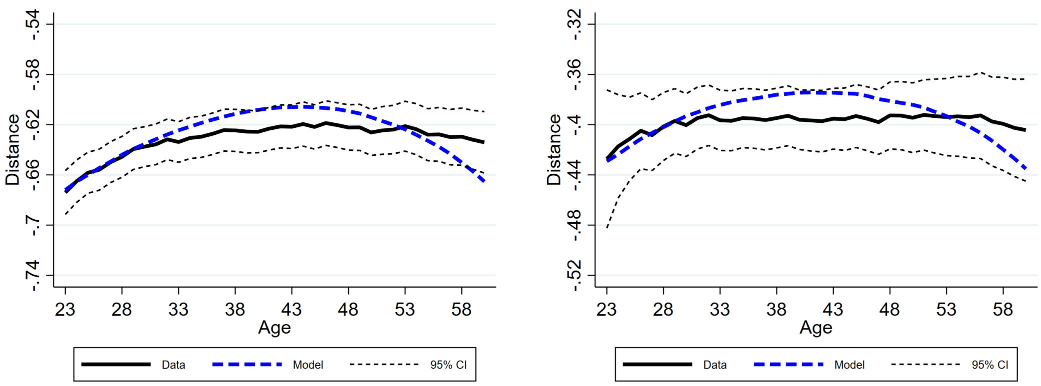


Note: Panel (a) shows the age profile of mean earnings for non-college workers and panel (b) is for college workers. The mean earnings of non-college workers at age 23 is normalized to 1 for comparison purposes. Panel (c) shows the age profile of variance of log earnings for non-college workers and panel (d) is for college workers.

Figure 9 shows that the model is able to match earnings profiles for both college and non-college workers. In particular, non-college workers' earnings growth over the life-cycle is 60% while the magnitude of growth is about 150% for college workers.

Figure 10: Technology Usage Profile

(a) Mean distance: non-college (b) Mean distance: college



Note: Panel (a) shows the age profile of the mean distance for non-college workers and panel (b) shows the age profile of the mean distance for college workers.

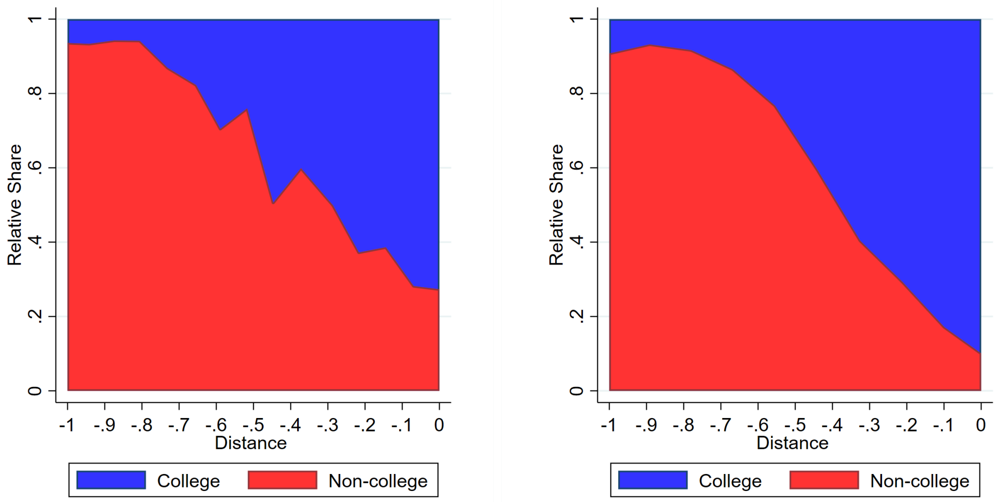
College workers on average experience steeper earnings growth because they have a higher baseline probability of human capital increase as shown Table B.1. This is the abstraction that college workers on average have higher learning ability relative to non-college workers.

Panel (c) and (d) show that the model generates increasing earnings inequality over the life-cycle for both educational groups. For non-college workers, the growth in life-cycle inequality is minor. The earnings dispersion profile slightly deviates from the data for college workers at the beginning of the life-cycle due to the timing of graduation. In the model, workers who choose the college path will graduate in four years and enter the labor market at age 23 uniformly. In reality, there is a substantial amount of students finishing bachelor's degrees in more than four years so the timing of entering the labor market also varies, which explains the dip in earnings dispersion profile as shown in the data. Other than that, the model is successful in replicating the growth in life-cycle inequality.

Figure 10 presents the model's performance on technology usage. The average distance profiles for both college and non-college workers are within the 95% confidence interval from the data. The model generates hump-shaped mean distance profiles for both college and non-college workers. The intuition is straightforward. At the early stage of the life-cycle, individuals have the incentive to upgrade technology since they can enjoy the benefit for the rest of the life-cycle. When approaching the end of the life-cycle, the cost of technology upgrades outweighs the benefit of working with advanced technologies. Consequently, workers gradually stop climbing up the technology ladder. This is also confirmed by the observation from Figure 7 panel (a) where old workers are more likely to choose technology downgrading.

Figure 11: Relative share of non-college workers (untargeted)

(a) Data (b) Model



Note: This figure shows the relative share of non-college workers over the technology distribution. Specifically, I divide the all technologies into 15 bins with equal width and calculate the relative share of non-college workers in each bin.

For validation, I examine untargeted moments: the relative share of college workers over the technology distribution. Figure 11 suggests that the model can replicate the joint distribution of technology usage and education. In particular, the relative share of non-college workers decreases with the technology level. The only unmatched part is that there are fewer non-college workers at the top of the technology distribution.

The decreasing relative share is mainly driven by the catch-up channel. Equation (20) suggests that staying at a higher technology position requires more effort and hence leads to higher disutility. Since this catch-up cost decreases with the human capital level, it implies that college workers on average face smaller cost as their human capital level is higher. So they are more likely to climb up the technology distribution.

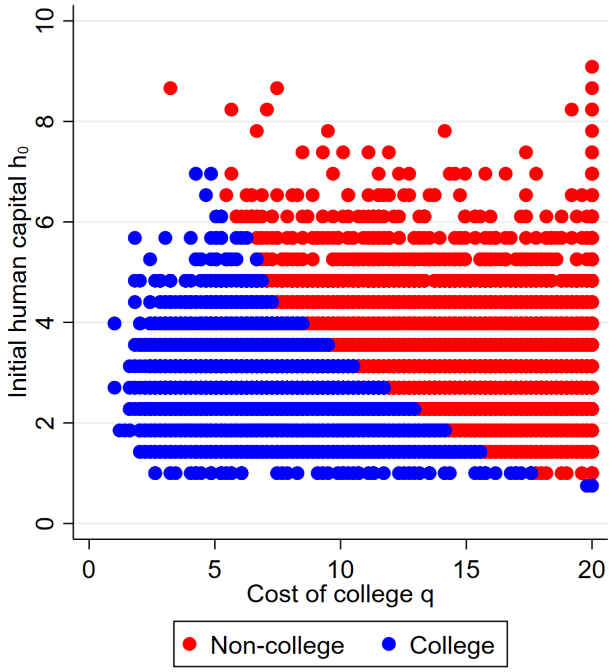
College decisions The college attainment decision is characterized by the combination of initial human capital h_0 and psychic q. Figure 12 shows the college decisions over the joint initial distribution. It is not surprising that people with higher cost q are less likely to attend college since it is directly associated with the disutility term during the college stage as shown in Equation (16). Moreover, people with low q would accumulate more human capital.

Given the same level of q, individuals with higher initial human capital are less likely to attend college. The reason is that the time cost of a college education exceeds the benefit of human capital investments. If one skips the college stage, he directly enters the labor market and gains earnings based on his initial human capital. If he decides to attend college, he must forgo four periods of the working stage. Even though he could accumulate additional human capital during the college stage, it cannot offset the sacrifice of four periods of earnings.

5 Technology and Life-Cycle Earnings

In this section, I first conduct counterfactual experiments to shut down each channel associated with technology separately and evaluate their effects on life-cycle earnings. Then I completely remove the choice of technology usage from the model and quantify

Figure 12: College decisions



Note: This figure shows the college decision based on the joint distribution of initial human capital (y-axis) and cost of a college education (x-axis). Blue dots denote people who attend college.

its aggregate impact on earnings growth and earnings inequality. The summary of results is shown in Table 3.

Results show that technology usage accounts for 31% of the growth in mean earnings and 46% of the growth in earnings inequality. Moreover, I find that the model generates a reinforcement mechanism between technology and human capital which amplifies earnings growth and earnings inequality over the life-cycle.

5.1 Catch-up channel

The first experiment is to shut down the catch-up channel by reducing catch-up cost. Since the entire technology distribution is moving forward, individuals have to pay catch-up cost $\phi_s(n,h,j)$ (in disutility term) to stay at the same relative position over

Table 3: Life-Cycle Earnings under Counterfactual Experiments

	% of college workers	Mean earnings growth (log points)	Growth in life-cycle inequality (log points)
Benchmark	29.8	59.4	12.3
Catch-up channel			
reduced by 50%	26.2	70.8	7.2
reduced by 100%	17.1	75.0	1.5
Direct channel			
reduced by 50%	21.8	46.0	7.4
reduced by 100%	17.8	41.5	5.5
Switching channel			
reduced by 100%	30.3	76.4	15.5
Eliminate the initial advantage	22.5	57.9	7.8
Remove technology usage	18.2	44.6	6.6

Note: Column 1 shows the fraction of people attending college in each scenario. Column 2 and 3 presents the growth in average earnings and earnings inequality (variance of log earnings) between age 60 and 23, measured in log points.
To reduce the catch-up (direct) channel by 50%, I set ϕ_0 (η) to be 50% of the original level. ϕ_0 or η is set to 0 to completely shut down each channel. To remove technology usage, I do not allow workers to switch technologies and shut down all three channels.

time with the functional form

$$\phi_s(n,h,j) = \phi_0(1+n)^{\phi_1} h^{\phi_2} \delta_s^{j-23} \tag{28}$$

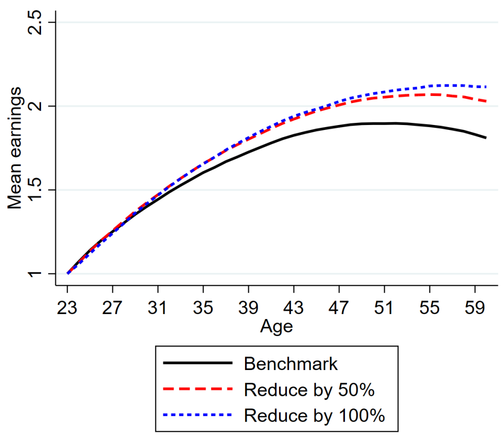
where ϕ_0, $\phi_1 > 0$ and $\phi_2 < 0$.

To reduce the catch-up channel by 50%, I set ϕ_0 to be half of the parameter in Table B.1. $\phi_0 = 0$ means completely shutting down the catch-up channel, i.e., the disutility term associated with technology usage disappears.

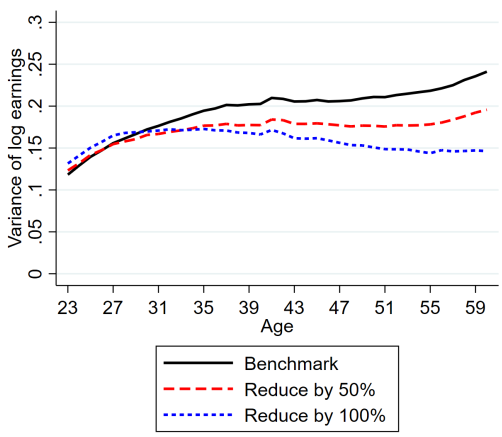
Figure 13 panel (a) suggests that reducing the catch-up channel increases earnings growth over the life-cycle. In particular, as shown in Table 3, the magnitude of earnings growth increases by 15.6 log points after shutting down the catch-up channel. The steeper growth is mainly driven by the change in technology usage patterns as shown in panel (c). Without the catch-up cost, workers face fewer barriers when switching to

Figure 13: Experiments with the Catch-up Channel

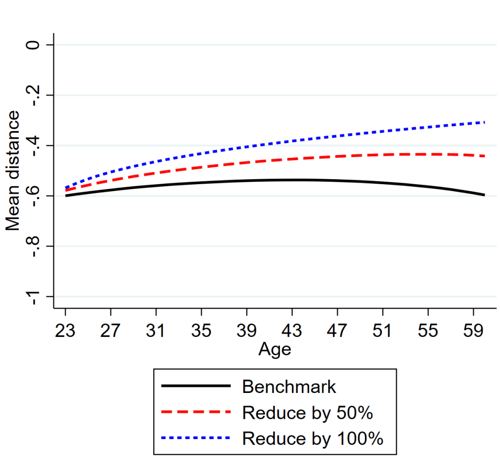
(a) Mean earnings



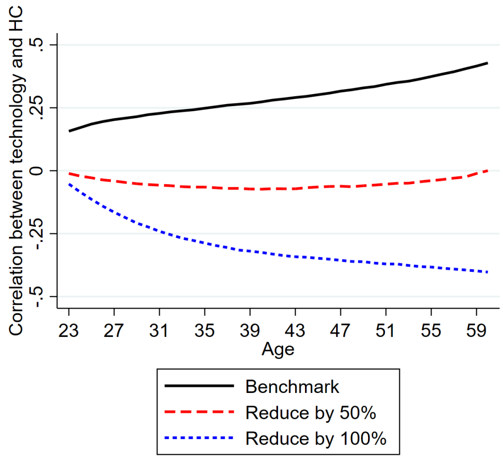
(b) Earnings inequality



(c) Mean distance



(d) Correlation between technology and HC



Note: The figure presents how life-cycle profiles change when reducing the catch-up channel. To reduce the catch-up channel by 50%, I set ϕ_0 to be 50% of the original level. ϕ_0 is set to 0 to completely shut down the catch-up channel. For comparison purpose, the mean earnings at age 23 are normalized to 1 in all scenarios in panel (a).

advanced technologies so they climb up the technology ladder at a faster pace. Consequently, the mean distance profile keeps increasing over the life-cycle even near retirement. Since technology level is positively associated with earnings, this leads to steeper earnings growth over the life-cycle.

Panel (b) in Figure 13 suggests that turning down the catch-up channel greatly reduces the growth in life-cycle inequality and the quantitative evaluation is presented in Table 3. In the benchmark economy, earnings inequality keeps increasing over the life-cycle and it is accompanied by a stronger correlation between technology and human capital as shown in panel (d). This observation confirms the reinforcement mechanism discussed in Section 3.6.1 where workers with high human capital are more likely to work with advanced technologies and vice versa. Therefore the increasing correlation amplifies the earnings dispersion over the life-cycle through the positive feedback loop.[12]

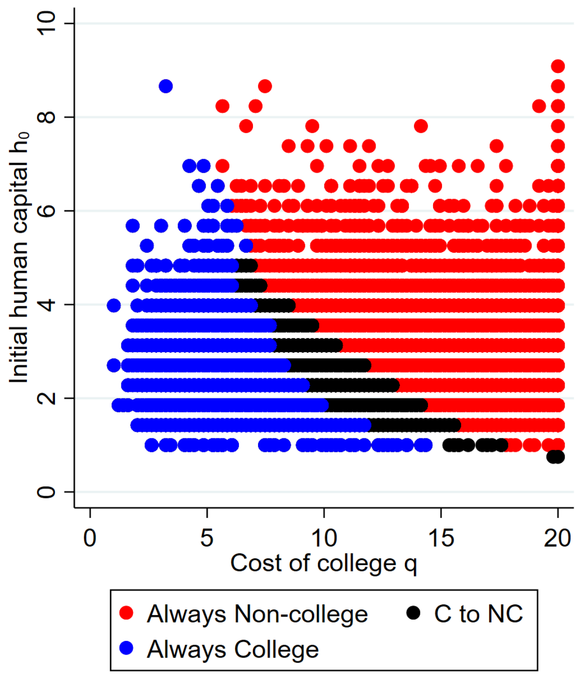
Reducing the catch-up channel weakens the impact of human capital on technology, which undermines the reinforcement mechanism and hence lowers the growth in earnings inequality. In the benchmark economy, the catch-up cost decreases with human capital so it is easier to upgrade technology for people with high human capital. So workers would be more stratified in the technology distribution on the basis of human capital. Once the catch-up cost is removed, human capital will not facilitate technology upgrading so there will be more people with low human capital switching to advanced technologies. Indeed, panel (d) shows that the correlation between technology and human capital is almost zero when the catch-up channel is reduced by 50%. The correlation even becomes negative after shutting down the catch-up channel.[13] This suggests that the amplification mechanism is weakened and therefore the growth in life-cycle inequality decreases.

[12]In Figure C.1, I also show that the changes in life-cycle inequality is not driven by the compositions effect, i.e. the change in the college attainment rate. The life-cycle inequality conditional on each educational groups decreases when shutting down the catch-up channel.

[13]Due to the switching channel, people with high human capital are less likely to switch since the loss in human capital is proportional. Therefore it forms a negative correlation between human capital and technology.

College decisions Table 3 shows that the college attainment rate drops 12.7 percentage points after shutting down the catch-up channel. To further understand the change in the attainment rate, Figure 14 compares college decisions between the benchmark model and the catch-up channel experiment. The black dots denote individuals who will go to college in the benchmark case ($\phi_0 = 3.1$) but decide not to attend college after shutting down the catch-up channel ($\phi_0 = 0$). In general, the threshold levels of cost q for a college education decreases, especially for people with low human capital.

Figure 14: College Decisions After Shutting Down the Catch-up Channel



Note: Always college stands for people who go to college in both cases. C to NC are people who go to the college in the benchmark case ($\phi_0 = 3.1$) but decide to skip college after shutting down the catch-up channel ($\phi_0 = 0$).

When catch-up cost is eliminated, people value human capital less because it is not beneficial for technology upgrading as discussed above. As a result, a college education becomes less attractive and the college attainment rate drops.

Moreover, the decline in the threshold level of q becomes larger for people with low initial human capital. This is because people with high human capital are less likely to be subject to the catch-up cost when upgrading technologies in the benchmark model. On the contrary, people born with low initial human capital are more likely to be deterred from upgrading because they cannot afford the catch-up cost due to low human capital. Therefore people with low human capital would like to attend college to accumulate additional human capital even though their cost q is relatively high.

Once the catch-up cost is eliminated, people with low human capital will face no barriers of technology upgrading so they can directly enter the labor market and climb up the technology ladder. Consequently, only people with extremely low cost q would like to attend college as they can accumulate a huge amount of human capital.

5.2 Direct channel

The direct channel means that earnings function is the product of technology level n and human capital h as described below

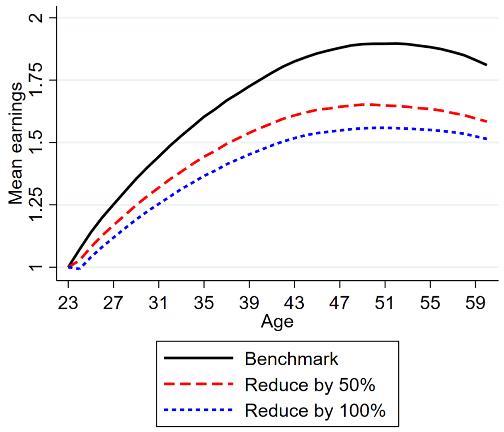
$$w = \exp(z) \cdot h \cdot \gamma^{(\eta \cdot n + t)} \tag{29}$$

This functional form explicitly generates a complementarity between human capital and technology.

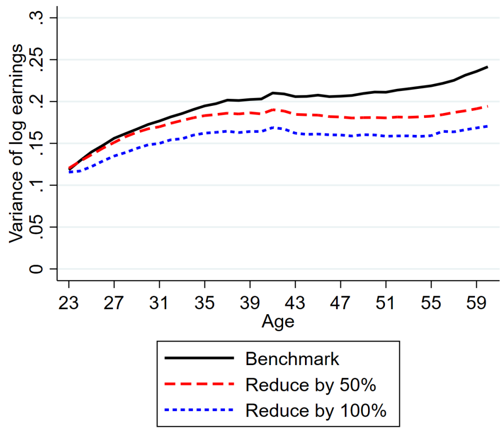
The parameter η governs the productivity difference within the technology distribution. To reduce the direct channel by 50%, I set η to be half of the calibrated value, which means that the earnings gap between the frontier technology and the least advanced technology shrinks 50%. Similarly, I shut down the direct channel by setting $\eta = 0$. In this extreme case, all technologies have the same productivity level as the frontier technology ($n = 0$). This also implies that technology does not complement human capital.

Figure 15: Experiments with the Direct Channel

(a) Mean earnings



(b) Earnings inequality



Note: The figure presents how life-cycle profiles change when reducing the direct channel. To reduce the catch-up channel by 50%, I set η to be 50% of the original level. η is set to 0 to completely shut down the catch-up channel. This implies that all technologies have the same productivity as the frontier technology. For comparison purpose, the mean earnings at age 23 are normalized to 1 in all scenarios in panel (a).

One caveat with the experiment of the direct channel is that lowering the parameter η also increases the level of earnings for people who do not use the frontier technology. This income effect might affect technology and human capital decisions at the aggregate level. To control for this possible channel, I multiply earnings function by a factor less than one such that the mean earnings at age 23 in each counterfactual is the same as the benchmark economy.

Figure 15 shows that shutting down the direct channel reduces the growth of life-cycle inequality and it also flattens the mean earnings profile. Specifically, Table 3 shows that the growth in mean earnings over the life-cycle decreases by 17.9. Moreover, the growth in life-cycle inequality decreases by 6.8 log points. In Figure C.2, I also show that the changes in life-cycle earnings profiles at the aggregate level is not mainly driven by the composition effect.

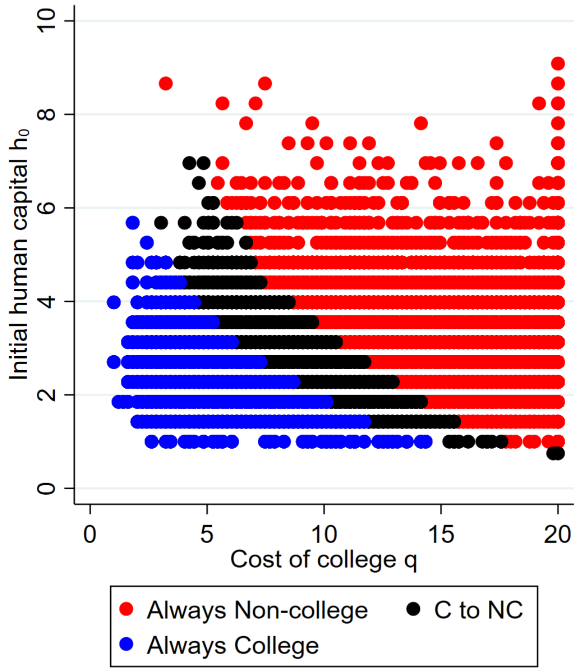
The intuition of flattened earnings inequality profile is similar to the experiment of the catch-up channel, i.e., the reduction in η also undermines the reinforcement mechanism. Specifically, shutting down the direct channel first eliminates the dispersion brought by technology usage and then compresses earnings dispersion through the complementarity term. Moreover, it closes the channel from technology to human capital since the incentive of human capital accumulation will not depend on the technology level now.

College decisions Figure 16 compares the college decisions between the benchmark model and the direct channel experiment. The black dots denote individuals who will go to college in the benchmark case ($\eta = 111$) but decide not to attend college after shutting down the direct channel ($\eta = 0$). In general, the threshold levels of initial human capital and cost q for a college education both decreases, which implies a college education is less attractive once technology has less impact on earnings.

The reduction in η affects the value of a college education mainly in two aspects. First, as the data suggested in Figure 6, college workers on average work with better technologies relative to non-college workers at the beginning of the life-cycle. The reduction in η weakens this initial advantage in technology because now people have higher earnings at the lower part of the technology distribution, which directly decreases the benefit of a college education.

Second, since the earnings gap across technologies shrinks, the importance of the interaction between technology and human capital also decreases. As a result, workers have less incentive to accumulate human capital so more people would skip the college stage and enter the labor market directly.

Figure 16: College Decisions After Shutting Down the Direct Channel



Note: Always college stands for people who go to college in both cases. C to NC are people who go to the college in the benchmark case ($\eta = 111$) but decide to skip college after shutting down the direct channel ($\eta = 0$).

5.3 Switching channel

The last interaction channel is the switching channel, where workers suffer human capital loss when switching to better technologies as shown in Equation (11). As shown in Table 3, shutting down switching channel increases the mean earnings growth to 76.4 log points and the growth in life-cycle inequality to 15.5 log points. The college attainment rate does not change significantly because the switching cost is proportional to human capital so it is not in favor of any specific educational groups.

Once the switching cost is removed, workers would upgrade technology more frequently so they experience steeper earnings growth over the life-cycle. In addition, the reinforcement mechanism becomes stronger so the life-cycle inequality also increases.

The intuition is the following. Since the loss in human capital is proportional to human capital, people with high human capital are less likely to make a huge step of technology upgrading. Once this barrier is removed, they would upgrade technology more intensively so the correlation between technology usage and human capital becomes stronger, which leads to a higher level of inequality and a steeper growth in life-cycle inequality.

5.4 Initial advantage

The above experiment indicates that technology plays an important role in determining college decisions. In this subsection, I disentangle the impact of technology on college decisions and conclude that the initial advantage in technology distribution is another key determinant. Once this advantage is eliminated, the college attainment rate drops from 29.8% to 22.5%.

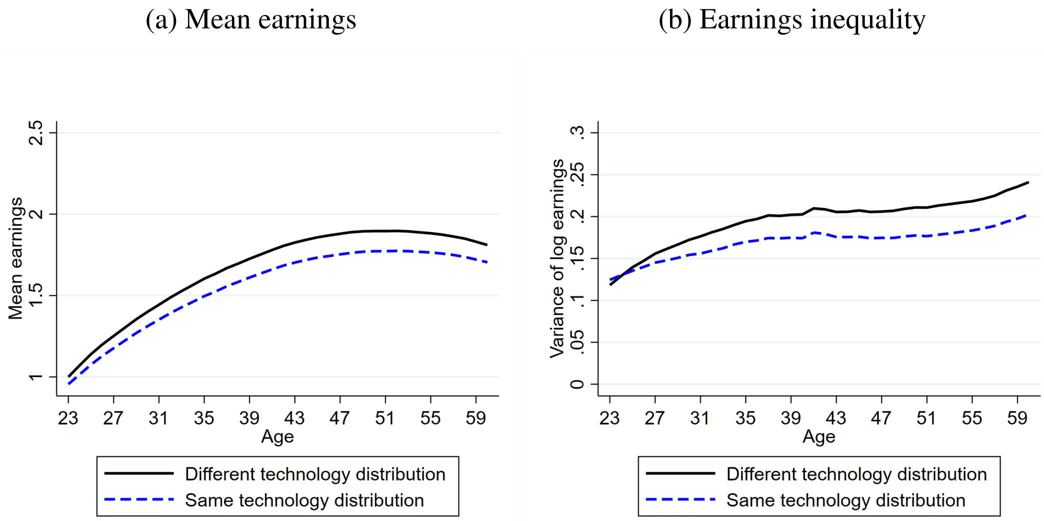
The empirical analysis shows that college workers on average work with better technologies relative to non-college workers at the beginning of the life-cycle and it is modeled as the difference in initial technology distributions presented in Figure 6. I shut down this channel by assuming that college workers also draw initial technology choices from the same distribution as non-college workers.

The second last row in Table 3 shows that the elimination of the initial advantage greatly reduces the college attainment rate. The intuition is also straightforward. When college workers lose it relative advantage in technology usage at the beginning of life-cycle, human capital investments become less attractive during the college stage. Therefore marginal workers will not go to college and enter the labor market directly.

Because of the composition effect[14], the magnitude of earnings growth decreases and the earnings inequality profile decreases over the life-cycle at the aggregate level as presented in Figure 17.

[14]From Figure 9, we know that non-college workers have flatter mean earnings profile and earnings inequality profile.

Figure 17: Elimination of the Initial Advantage



Note: The figure presents life-cycle profiles when both educational groups draw initial technology choice from the same distribution (as non-college workers). In panel (a), the mean earnings at age 23 is normalized to 1 in the benchmark economy.

5.5 All together

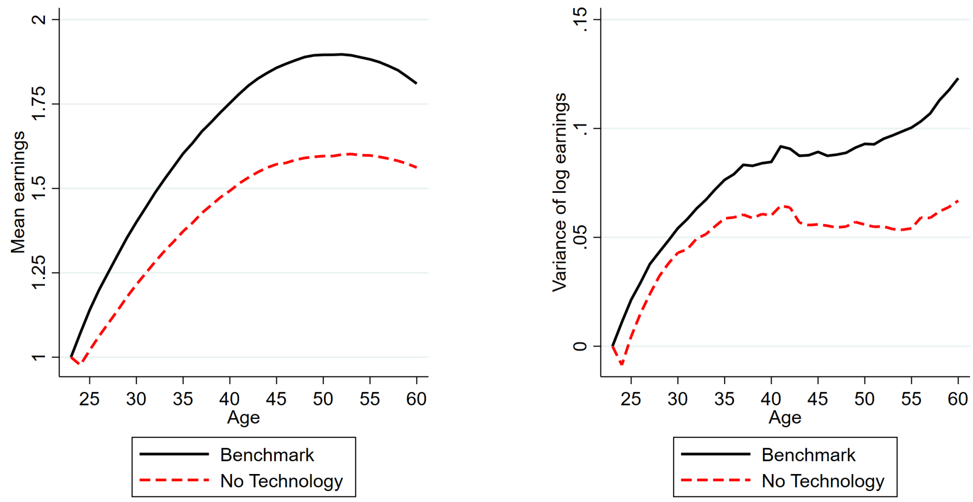
Lastly, I turn down all interaction channels associated with technology and evaluate how life-cycle earnings change. In particular, I do not allow workers to switch technologies and shut down the catch-up cost associated with technology usage. Besides, I shut down the direct channel by equalizing productivity levels across all technologies such that the mean earnings at age 23 is the same as the benchmark economy.

The model boils down to a risky human capital investments model where life-cycle earnings are only determined by endogenous human capital investments (at college and during the working stage) and idiosyncratic shocks. The difference between life-cycle earnings profiles can be interpreted as the contribution of technology usage.

As shown in Figure 18 and Table 3, after removing technology usage, the growth in mean earnings decreases by 14.8 log points (25%). In addition, the growth in earnings

Figure 18: Remove Technology Usage

(a) Mean earnings (b) Earnings inequality



Note: The figure presents life-cycle profiles after removing technology usage from the benchmark model. The mean earnings at age 23 is normalized to 1 in panel (a) and the level of earning inequality at age 23 is normalized to 0 in panel (b).

inequality decreases by 5.7 log points (46%) over the life-cycle, which is larger than the number (38%) obtained from the reduced-form analysis in Section 2.3. Moreover, the fraction of college workers drops from 29.8% to 18.2%.

One caveat with the final result is that it is not additive because each experiment might be intertwined with other channels. For example, shutting down the direct channel also implicitly assumes that the initial advantage is eliminated. In addition, the effect of the catch-up channel on life-cycle inequality is much larger than the overall impact. This is because the catch-up experiment does not isolate the effects of the switching channel, which in turn increases the growth in life-cycle inequality.

6 Policy Analysis: Non-linear Taxation

In this section, I investigate the role of technology usage in non-linear taxation. Recent findings in the literature show that a more progressive tax distorts the incentive of human capital accumulation and hence decreases earnings growth.[15] I find that these distortionary effects on college attendance and earnings growth are larger with the presence of technology usage. That is, the reinforcement mechanism between technology and human capital discussed above amplifies the impact of a progressive tax.

To reach this conclusion, I evaluate the effects of progressive taxes in two scenarios: with and without technology usage. In particular, I re-parameterize the model without technology usage, as mentioned in Section 5.5, to match the same set of moments except for technology usage. Then I replace the proportional tax on labor earnings with a progressive tax in both models and compare the effects on life-cycle earnings.

6.1 Progressive tax system

In the baseline model, individuals' labor earnings and capital income are taxed at a flat rate τ. I now replace the proportional tax rate on labor earnings with progressive taxes and leave the tax rate on capital income unchanged.

I borrow the progressive tax system pioneered by Feldstein (1969) and later popularized by Benabou (2002). In particular, the average tax rate on labor earnings is given by

$$\tau(w) = 1 - \lambda (w/\bar{w})^{-\tau_p} \tag{30}$$

where $\bar{w}$ is the mean labor earnings in the economy. The average tax rate of the individual with mean labor earnings is $1-\lambda$. This tax rate increases with labor earnings w in a concave pattern since $\tau_p > 0$.

[15] See Erosa and Koreshkova (2007) and Guvenen et al. (2014) for exmaple.

The parameter λ controls for the level of the tax rate and the parameter τ_p stands for the progressivity in the tax schedule. In the case of $\tau_p = 0$, the average tax rate will not depend on labor income, i.e., it boils down to the standard proportional tax.

A higher τ_p means the tax system is more progressive. In the following counterfactual analysis, I consider three levels of progressivity as shown in Table 4. The least progressive tax schedule is $\tau_p = 0.05$, which is around the level estimated by Guner et al. (2014) using data on federal tax returns in 2000. The second scenario is $\tau_p = 0.10$, a number estimated by Heathcote et al. (2020) where they additionally include government transfers alongside taxes. The last case with $\tau_p = 0.15$ stands for the level of progressivity in European countries, like the U.K. or Germany.[16]

6.2 An alternative model without technology usage

To evaluate the role of the technology channel, I conduct the same policy experiments in two scenarios: model with and without technology usage. The model without technology corresponds to the one discussed in Section 5.5 with re-parameterization to match life-cycle profiles of earnings.

In particular, I solve for an alternative model where workers are not allowed to switch technologies over the life-cycle. Furthermore, technologies are indifferent in terms of productivity. To sum up, in this alternative model, life-cycle earnings are only driven by endogenous human capital investments and idiosyncratic shocks.

The parameters associated with human capital are re-calibrated to match life-cycle profiles of mean earnings and earnings inequality as well as the college attainment rate. The parameters related to idiosyncratic shocks remain the same as in the baseline model for comparison purposes. Details can be found in Section B.3.

[16] See Heathcote et al. (2020) for details.

6.3 Tax progressivity and earnings over the life-cycle

I conduct policy experiments to explore how progressivity affects earnings over the life-cycle with and without technology usage. The results in Table 4 indicate that a more progressive tax system leads to a lower college attainment rate and a smaller earnings growth over the life-cycle. Furthermore, these distortionary effects are smaller in the alternative model without technology.

Table 4: How Progressivity Affects Life-Cycle Earnings

Progressivity	% of college workers	Mean earnings growth (log points)	Growth in life-cycle inequality (log points)
Proportional tax: benchmark economy			
τ_p =0	29.8	59.4	12.3
Progressive tax			
Model *with technology*			
$\tau_p = 0.05$	25.9	55.1	11.6
$\tau_p = 0.10$	22.3	50.5	11.0
$\tau_p = 0.15$	18.9	45.9	10.2
Model *without technology*			
$\tau_p = 0.05$	26.4	56.7	11.7
$\tau_p = 0.10$	23.0	52.5	11.1
$\tau_p = 0.15$	19.8	50.2	10.4

Note: This table presents how earnings change with respect to the progressivity (τ_p) under two scenarios: model with and without technology usage. Column 2 shows the mean earnings growth from age 23 to 60 at the aggregate level, measured in log points. Column 3 shows the change in the variance of log earnings, measured in log points, between age 23 and 60. Total taxes collected by the government are constant in each scenario.

6.3.1 In the baseline model

In the baseline model with technology usage, when the proportional tax is replaced with a progressive tax at the U.S. level ($\tau_p = 0.05$), the growth in life-cycle earnings decreases by 4.3 log points and the college attainment rate drops by 3.9 percentage points. Moreover, the growth in life-cycle inequality decreases by 0.7 log points. The decreases in earnings growth and college attainment rate are higher when the progressivity increases to a European level ($\tau_p = 0.15$).

These findings are consistent with the common view in the literature that progressive taxes distort the incentive to accumulate human capital.[17] Since the marginal tax rate increases with earnings, the marginal benefit of human capital investments decreases as a larger fraction of income would be taxed. Therefore fewer people decide to go to college and people make less human capital investments during the working stage. This is confirmed by the observation in Figure 19 panel (b) where human capital is flatter when the progressivity is higher.

In addition to human capital, progressive taxes also suppress the incentive of technology upgrading, and intuition is the same as the argument for human capital accumulation. Panel (c) suggests that the mean distance profile shifts downward when taxes become more progressive, which implies that people on average use less advanced technologies over the life-cycle. In particular, the average distance drops more than -0.05 at age 60 when switching from $\tau_p = 0.05$ to $\tau_p = 0.15$. The magnitude is equivalent to 0.4 times the standard deviation of the distance at age 23. Since earnings are a function of human capital and technology, panel (b) and (c) in Figure 19 together imply a flatter growth in life-cycle earnings if the tax system becomes more progressive.

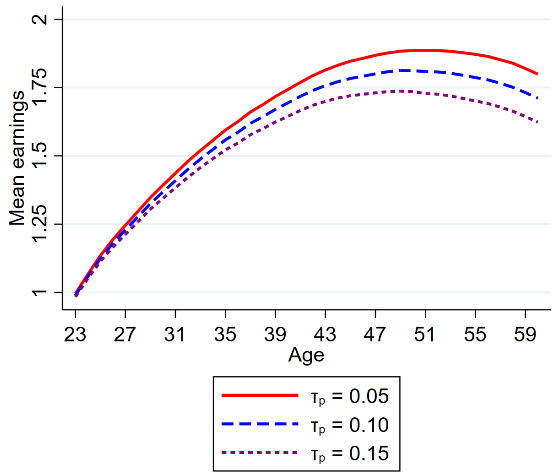
One potential reason behind the flattening of earnings profile is the composition effect, i.e., the decline in the college attainment rate. Since non-college workers have a flatter mean earnings profile, the drop in the college attainment rate naturally leads to a flatter earnings profile at the aggregate level. To rule out this possibility, I also look at the life-cycle profiles for both college and non-college workers respectively and the results show that the progressive taxes do disincentivize human capital accumulation and technology upgrading for both educational groups.

As presented in Figure C.3 and Figure C.4 panel (a), the growth in life-cycle earnings

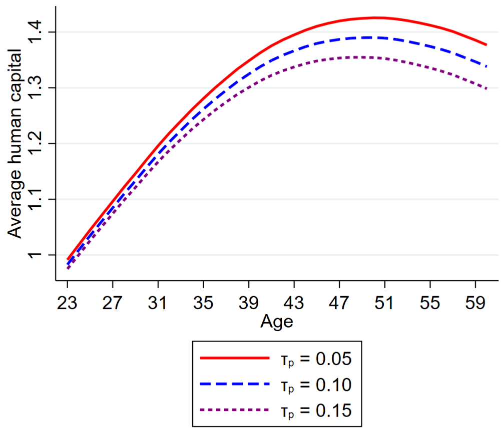
[17] See Guvenen et al. (2014), Krueger and Ludwig (2016), and Badel et al. (2020) for example.

Figure 19: Earnings Profiles under Progressive Taxes

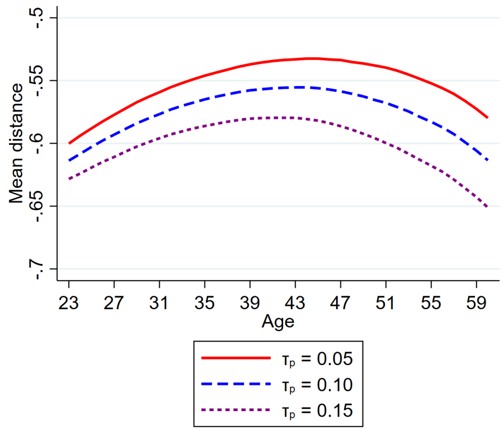
(a) Mean earnings



(b) Mean human capital



(c) Mean distance



Note: Panel (a) shows the average earnings profile over the life-cycle and panel (b) shows the average human capital profile. Both values at age 23 are normalized to 1 when $\tau_p = 0.05$. Panel (c) presents the mean distance profile, i.e., the average technology usage profile. A higher τ_p implies a more progressive tax schedule.

decreases with the progressivity for both educational groups. Panel (b) and (c) show that workers have less incentive to accumulate human capital and upgrade technology when facing a more progressive tax regardless of education. Therefore, the flattening of the earnings profile is not solely driven by the change in the college attainment rate.

6.3.2 In the alternative model without technology

Now I turn to the alternative model without technology usage and evaluate the same set of policy experiments. The last three rows in Table 4 show that progressive taxes generate smaller distortionary effects on earnings growth and earnings inequality without the presence of technology. In other words, technology usage amplifies the impact of a progressive tax on earnings growth and earnings inequality.

When the economy switches from a proportional tax to a progressive tax at a European level ($\tau_p = 0.15$), earnings growth only decreases by 9.2 log points, which is 32% smaller than the change in the baseline model with technology usage (13.5 log points). Moreover, the decline in the college attainment rate is only 10 percentage points, which is also smaller than the decline in the benchmark scenario.

The impact on life-cycle inequality under different progressivity is relatively smaller compared to earnings growth. Specifically, when switching from proportional tax to a progressive tax at a European level, the growth in life-cycle inequality decreases by 2.1 log points in the baseline model while the decline is 1.9 log points in the alternative model. Overall, the distortionary effects of a progressive tax are smaller in the model without technology usage.

To further understand the difference in policy implications, I focus on how progressivity shapes human capital accumulation over the life-cycle since parameters related to idiosyncratic shocks are fixed in both models. In Table 5, I present human capital growth rates under different progressivity relative to the proportional tax in two models. For example, when the economy switches to a progressive tax with $\tau_p = 0.05$, the

Table 5: Human Capital Growth Relative to Proportional Tax

Progressivity	Aggregate	College workers	Non-college workers
Model *with technology*			
$\tau_p = 0.05$	71.9%	57.8%	87.5%
$\tau_p = 0.10$	67.4%	54.9%	83.3%
$\tau_p = 0.15$	62.6%	52.8%	78.0%
Model *without technology*			
$\tau_p = 0.05$	93.4%	94.9%	94.9%
$\tau_p = 0.10$	86.3%	88.5%	89.6%
$\tau_p = 0.15$	78.7%	82.5%	82.6%

Note: This table presents how human capital growth changes with respect to the progressivity (τ_p) relative to the benchmark mark case with proportional tax under two scenaiors: with and without technology usage. The column 2 shows the relative growth for the economy and column 3 and 4 shows the relative changes conditional on education.

growth in human capital between age 23 and 60 (measured in log points) decreases to 71.9% relative to the growth in the proportional tax in the baseline model with technology usage. In particular, the growth for college workers is affected more, decreasing to 57.8%, compared to non-college workers (87.5%).[18]

Table 5 shows that human capital growth is less distorted by a progressive tax in the alternative model without technology usage. For instance, when the economy switches to the same progressivity level $\tau_p = 0.05$, the growth in human capital only decreases to 93.4% relative to the growth in the proportional tax in the alternative model without technology usage, which is much smaller than the change in the baseline model (71.9%). To sum up, the distortionary effects of a progressive tax are smaller in the alternative model without technology usage for both college and non-college workers.

The intuition behind these results is similar as discussed above. In the baseline model with technology, a progressive not only distorts the incentive to human capital investments but also suppresses the benefit of technology upgrading, which further

[18]The levels of growth rates are not comparable between the baseline model and the alternative model since the model without technology usage is reparameterized to match the same set of life-cycle moments. Therefore I compare how the growth rate change relative to the case with proportional tax.

dampens human capital accumulation through the reinforcement mechanism. Therefore ignoring technology usage channel results in an underestimation of policy implications on progressive taxes.

7 Final Remarks

In this paper, I thoroughly quantify the contribution of technology to earnings through the lens of a life-cycle model with a college decision, endogenous technology usage, and human capital investments. The novelty of the model is to allow for rich interactions between human capital and technology. In particular, human capital facilitates technology upgrading through the *catch-up channel*. The *direct channel* makes human capital accumulation investments contingent on technology as it leads to the complementarity between these two factors in earnings. Moreover, the *switching channel* captures the barrier to technology upgrading in terms of the loss of human capital.

My model suggests that technology usage accounts for 25% of the growth in mean earnings and 46% of the growth in earnings inequality over the life-cycle. Furthermore, counterfactual experiments suggest that both catch-up channel and direct channel are crucial in generating increasing earnings inequality over the life-cycle. Specifically, these two channels build up a reinforcement mechanism between technology and human capital where workers with high human capital are more likely to work with advanced technologies and vice versa. The interaction between these two terms amplifies the earnings dispersion over the life-cycle.

Furthermore, I find that technology usage amplifies the impact of a progressive tax on earnings growth and college attainment. Recent studies show that a more progressive tax depresses human capital accumulation and hence lowers earnings growth. I find that the distortionary effects are larger with the presence of endogenous technology usage compared to a standard human capital model.

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A The Construction of the Distance to the Frontier

I use a combination of inputs from the O*NET data set to construct the index to measure technology usage at the individual level. The O*NET data set provides detailed information on the importance of knowledge, tasks and skills for each occupation. In particular, a random sample of workers chooses the description that best fits their daily work in one specific aspect (for example programming skills). The answers are on a scale from 1 ("not important") to 6 ("extremely important"). The index of importance for that occupation is the average responses from the sample of workers.

I extract indices of the following characteristics: knowledge about computers and electronics, activities interacting with computers, programming skills, systems evaluation skills, quality control analysis skills, operations analysis skills, activities with updating and using relevant knowledge, technology design skills, activities analyzing data and information, activities processing information, knowledge with engineering and technology, and activities managing material resources.

I sum all the values from the above characteristics and normalize the sum to the interval $[-1,0]$. The normalized index is denoted as the *distance to the frontier*. By construction, it measures how intensively workers use information technology at their daily work. The occupation that uses information technology most intensively is considered to be the frontier technology and its distance to the frontier is 0.

B Parameterization

I first choose a collection of parameters from exogenous source. The rest of parameters are jointly calibrated to match the life-cycle profiles of earnings and technology usage for both educational groups. The parameters are listed in Table B.1.

Table B.1: Parameters

Category	Meaning	Parameter
Externally chosen parameters		
Demographic	population growth rate	$\mu = 0.0012$
	rate of return on asset	$r = 0.047$
	life expectancy and retirement age	$J = 75$, $J_R = 64$
Tax	proportional tax rates on income	$\tau = 0.15$, $\tau_{ss} = 0.1$
Technology	growth rate of the technology distribution	$\gamma = 1.005$
	productivity difference within the technology distribution	$\eta = 111$
Initial distribution of tech	approximated by Beta distribution from the data	
Internally chosen parameters		
Preference	discount factor	$\beta = 0.988$
	disutility of human capital investments	$\xi = 0.25$
Human capital	human capital grid	$h_{min} = 1$, $h_{max} = 17.6$
	baseline probability of human capital increase	$p_C = 0.35$, $p_{NC} = 0.23$
	human capital decrease parameter	$\alpha_C^{down} = 0.15$, $\alpha_{NC}^{down} = 0.07$
	depreciation	$\rho = 0.99$
	human capital production at college stage	$\alpha_h = 0.35$
Productivity shocks	size of innovation	$\sigma_z = 0.132$, $\sigma_C^{\varepsilon} = 0.143$, $\sigma_{NC}^{\varepsilon} = 0.131$
	persistence of shocks	$\rho_C^z = 0.95$, $\rho_{NC}^z = 0.92$
Catch-up cost	disutility associated with technology usage	$\phi_0 = 3.14$, $\phi_1 = 1.5$, $\phi_2 = -1.3$
	age adjustment in disutility	$\delta_C = 0.994$, $\delta_{NC} = 0.999$
Initial distributions	initial human capital h_0	$\mu_{h_0} = 1.01$, $\sigma_{h_0} = 0.1$
	physic cost of college q	$\mu_q = 2.91$, $\sigma_q = 0.5$
	initial productivity z	$\mu_{z_0} = 0$, $\sigma_{z_0} = 0.13$

Note: This table presents parameters used in the benchmark economy. The first set of parameters is chosen from external sources. The second set of parameters is jointly determined to match the life-cycle profiles of mean earnings, variance of log earnings and mean distance for both college and non-college workers as well as the average college attainment rate.

B.1 Parameters chosen from external source

Demographics The life-cycle starts from age 18 to 75 but I only focus on the life-cycle statistics from age 23 to 60. Individuals retire after age 64 and live another 10 periods. The annual population growth rate is 1.2%, which is the geometric average over the period 1959–2007 from the Economic Report of the President (2008). I assume it is a small open economy where the interest rate is set exogenously to be 0.047 so the after-tax interest rate is 4%.

Tax and social security In the benchmark model, I set the flat tax rate τ on income to be 0.15, which is the approximation of the tax rate in the U.S. once itemizations, deductions and income-contingent benefits are considered. The tax rate of social security on labor earnings is 0.1, which is close to the average rate in the period of analysis.

I assume the social security benefits for college workers are 17% higher than non-college workers:

$$b_C^{ss} = 1.17 b_{NC}^{ss} \tag{31}$$

This number is borrowed from Guner et al. (2021) where they document how social security benefits vary across household types and educational types.

B.2 Parameters chosen internally

The rest of the parameters except for the discount factor β are jointly chosen to match (1) the fraction of college workers, (2) life-cycle profiles of mean earnings, mean distance and the variance of log earnings for both college and non-college. I denote the set of 24 parameters as Γ. Since I target the entire life-cycle profiles, the number of parameters is much smaller than the number of targeted moments.

Formally, the parameterization strategy is to minimize the distance between moments generated by the model and moments from the data. The minimization problem is described below:

$$\min_{\Gamma} \sum_{s=NC,C} \left[\sum_{j=23}^{60} \left((\frac{A_{j,s}^m - A_{j,s}^d}{A_{j,s}^d})^2 + (\frac{B_{j,s}^m - B_{j,s}^d}{B_{j,s}^d})^2 + (\frac{C_{j,s}^m - C_{j,s}^d}{C_{j,s}^d})^2 \right) \right] + (\frac{\omega^s - \omega^d}{\omega^d})^2$$

where $A_{j,s}^m$ is the mean log earnings of workers at age j from $s \in \{C, NC\}$ educational group simulated by the model and $A_{j,s}^d$ is the counterpart from the data. $B_{j,s}^m$ and $C_{j,s}^m$ stand for variance of log earnings and mean distance respectively. ω^m is the fraction of college workers in the model and ω^d is the counterpart from the data.

Lastly, I set the discount factor β to match the ratio between median asset and median labor income. The target ratio is 2.5, which is taken from the Survey of Consumer Finances (SCF) 2013.[19] The discount factor β is chosen to be 0.988 and it generates the

[19] Labor income w corresponds to earnings and asset a corresponds to wealth in the SCF .

ratio between median asset and median labor income of 2.6 in the model.

Human capital process Human capital levels are discrete and represented by an evenly spaced ordered set $[h_{min}, ..., h_{max}]$. The lowest level is normalized to 0 and the highest level is 17.6. I set the number of human capital levels to be 41, which is the same length as the working stage. The rationale is that it would take the whole working stage to climb from the lowest level to the highest level since the accumulation of human capital is stepwise. The rest of the parameters are set to match mean earnings profiles and earnings dispersion profiles. The return of human capital production α_h is chosen to match the earnings difference between college workers and non-college workers at age 23.

The parameterized values indicate that college workers have a higher baseline probability of human capital increase. This is in line with the results from the literature on college attainment where they find the average learning ability is higher among college workers. As a result, college workers on average accumulate human capital faster than non-college workers.[20] In addition, the parameter that governs human capital decrease (α^{down}) is also higher for college workers, which is to match the depreciation near retirement since the depreciation rate is the same across education.

Productivity shocks The size of shocks drawn over the technology distribution in each period is $\sigma_z = 0.132$ and this applies to both education groups. The parameterized size of innovation of AR(1) process for college and non-college workers are 0.143 and 0.131 respectively. The persistence parameter for college and non-college workers are 0.95 and 0.92. These values are in the ballpark of the empirical estimation by Guvenen (2009). In addition, the values suggest that college workers experience larger and more

[20] In Keller (2014) and Kong et al. (2018), the learning ability affects the marginal return to effort in the human capital production function. People with high learning ability would be sorted into the college path and they will make more investments during the college stage. As a result, the average learning ability of college workers is higher.

persistent shocks relative to non-college workers, which is also supported by findings from Guvenen (2009).

One caveat in interpreting productivity socks is that the realized shocks are the combination of technology decisions and the AR(1) process. As discussed in Section 3.6.1, one can easily "reset" his productivity by switching to new technology. In fact, the opportunity of switching technologies can help workers to avoid a sequence of negative shocks.[21] So the realized sequence of shocks is less persistent than the parameters of the AR(1) process suggest.

Initial distribution The initial distributions of human capital h_0 and q are crucial to pin down the college attainment rate. Furthermore, the distribution of initial human capital h_0 is important to generate the levels of inequality in earnings at the beginning of the life-cycle for both educational groups. Besides, the distribution of q governs how college workers accumulate human capital during the college stage, which also generates necessary variation in earnings within college workers.

B.3 Parameterization in the alternative model

Table B.2 shows the parameters that are re-calibrated in the alternative model without technology usage. In particular, I leave parameters associated with shocks unchanged and only modify the ones related to human capital production both in college and working stage. The discount factor is also chosen to match the ratio between median asset and median earnings in the economy. The parameters that are not shown in Table B.2 remain the same values as Table B.1.

[21] This view is close to the literature on occupational mobility, e.g., Dillon (2018) and Liu (2019).

Table B.2: Re-calibrarted Parameters

Category	Meaning	Parameter
Preference	discount factor	$\beta = 0.991$
Human capital	baseline probability of human capital increase	$p_C = 0.45$, $p_{NC} = 0.22$
	human capital decrease parameter	$\alpha_C^{down} = 0.16$, $\alpha_{NC}^{down} = 0.06$
	human capital production at college stage	$\alpha_h = 0.30$
Initial distributions	initial human capital h_0	$\mu_{h_0} = 0.90$, $\sigma_{h_0} = 0.066$
	physic cost of college q	$\mu_q = 3.08$, $\sigma_q = 0.98$
	initial productivity z	$\mu_{z_0} = 0$, $\sigma_{z_0} = 0.084$

Note: This table presents parameters used in the alternative model without technology usage. Parameters that are not shown in this table remain the same values as in the benchmark model.

C Life-cycle Profiles Conditional on Educational Group

In this part I present the life-cycle earnings profiles in the counterfactual experiments conditional on educational group. In Figure C.1, I present the conditional life-cycle earnings profiles when shutting down the catch-up channel. The mean earnings growth increases for educational groups and the life-cycle inequality decreseas for both educational groups. Therefore the change at the aggregate level is not only driven by the compositional effect.

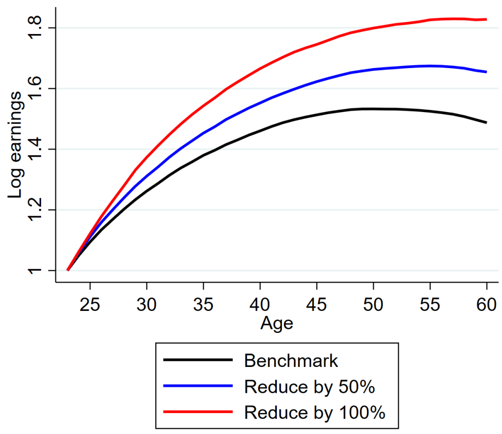
However, the change in mean earnings for college workers is not monotone in the sense that the mean growth is larger when the catch-up cost is reduced by 50%. When there is not catch-up cost, college workers will upgrade technology more frequently so they suffer more human capital loss. So the growth in mean earnings slightly declines but the absolute level of earnings increases.

Similarly, Figure C.2 shows the conditional life-cycle earnings profiles when shutting down the direct channel. The mean earnings growth and life-cycle inequality both decreases for each educational group, which also indicates that the change at the aggregate level is not only driven by the compositional effect.

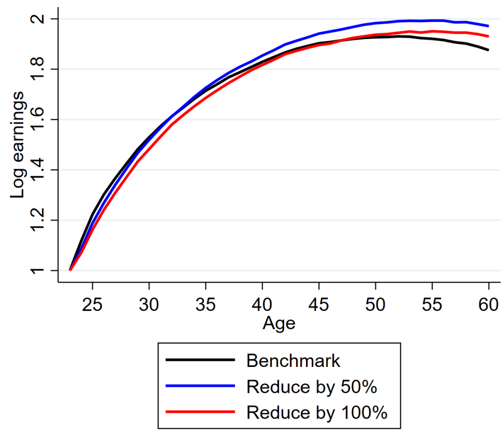
Figure C.3 and Figure C.4 show the conditional life-cycle earnings profiles under taxation experiment. A more progressive depresses mean earnings growth and distorts the incentive for human capital accumulation and technology upgrading for both college and non-college workers.

Figure C.1: Experiments with the Catch-up Channel

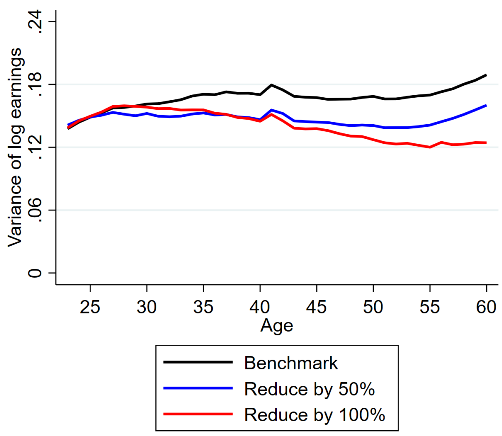
(a) Mean earnings: non-college



(b) Mean earnings: college



(c) Earnings dispersion: non-college



(d) Earnings dispersion: college

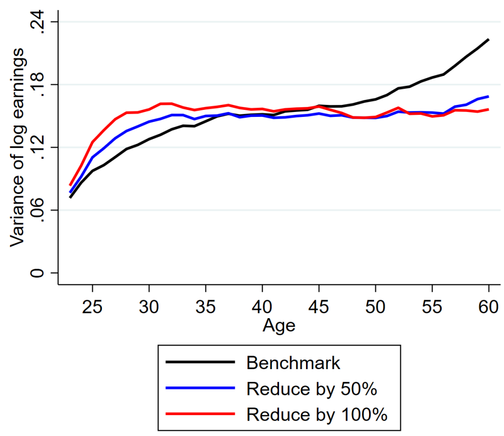
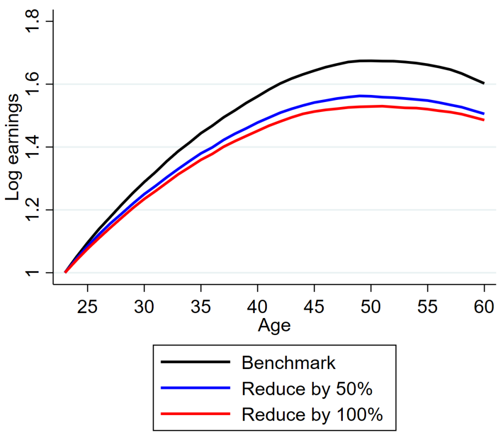
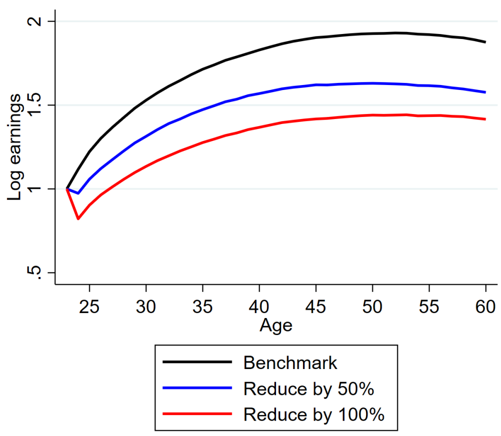


Figure C.2: Experiments with the Direct Channel

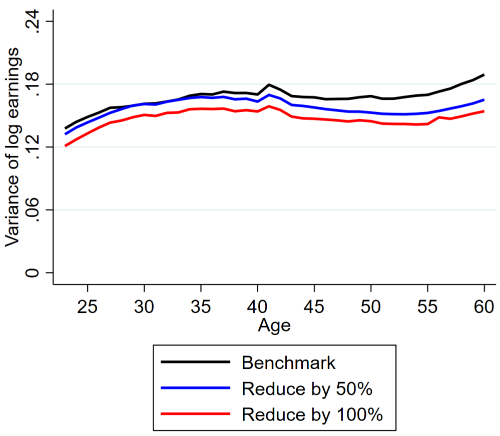
(a) Mean earnings: non-college



(b) Mean earnings: college



(c) Earnings dispersion: non-college



(d) Earnings dispersion: college

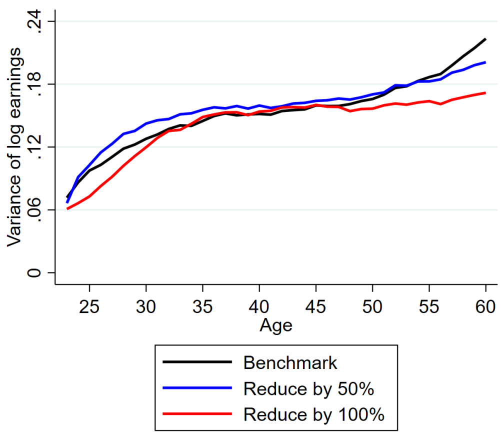
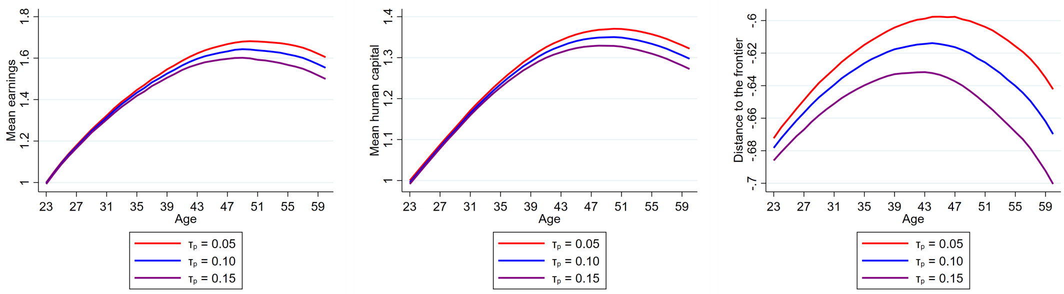


Figure C.3: Earnings profiles under progressive taxes (non-college workers)

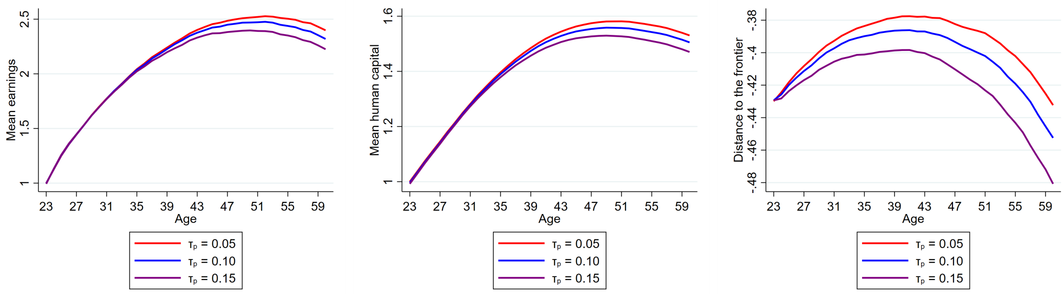
(a) Mean earnings (b) Mean human capital (c) Mean distance



Note: Panel (a) shows the average earnings profile over the life-cycle and panel (b) shows the average human capital profile. Both values at age 23 are normalized to 1 when $\tau_p = 0.05$. Panel (c) presents the mean distance profile, i.e., the average technology usage profile. A higher τ_p implies a more progressive tax schedule.

Figure C.4: Earnings profiles under progressive taxes (college workers)

(a) Mean earnings (b) Mean human capital (c) Mean distance



Note: Panel (a) shows the average earnings profile over the life-cycle and panel (b) shows the average human capital profile. Both values at age 23 are normalized to 1 when $\tau_p = 0.05$. Panel (c) presents the mean distance profile, i.e., the average technology usage profile. A higher τ_p implies a more progressive tax schedule.