The College Premium Rollercoaster and the Rebound of Lifetime Wage Growth: A Structural Analysis[*]

Raquel Fonseca[†] Etienne Lalé[‡] François Langot[§]
Thepthida Sopraseuth[¶]

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Abstract

We develop a general-equilibrium OLG model of human capital to study the dynamics of the U.S. college premium and lifetime wage profiles between 1940 and 2020. The model features endogenous education and on-the-job training, along with exogenous aggregate (skill-neutral and skill-biased) shocks and cohort-specific trends in initial human capital endowments and learning capabilities. The estimated model replicates the W-shaped evolution of the college premium and the flattening then steepening of lifetime wage profiles. We show that changes in labor efficiency, rather than changes in relative skill prices, are the main driver of these dynamics. We quantify the contribution of the estimated exogenous drivers and find a key role for the deterioration of human capital endowments and learning abilities among more recent cohorts. Crucially, endogenous adjustments in educational attainment and skill prices serve as powerful equalizing forces. Without these market mechanisms, the gap between the lifetime wage profiles of skilled and unskilled workers would widen and the college premium double.

Keywords: College premium, Life-cycle wage profile, On-the-job training, Human capital, Technological progress

JEL Classification: E24, E25, J24, J31

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[†]ESG-Université du Quebec à Montreal & CIRANO

[‡]York University, Canada

[§]Le Mans University (GAINS-TEPP & IRA), IUF, Paris School of Economics, Cepremap & IZA

[¶]CY Cergy-Paris University, Thema

1 Introduction

This paper analyzes the evolution of the U.S. college wage premium and lifetime wage growth since 1940 through the lens of a structural, general equilibrium OLG model of human capital. We argue that understanding these patterns requires a nonstationary framework featuring aggregate technology shocks, cohort-specific human capital dynamics, and market-wide interactions. Our main contribution is to show that changes in the quality of workers, as captured through human capital endowments and learning capabilities, are more central to explaining wage inequality in the post-WWII era than changes in the relative skill prices.

Stylized facts. Our starting point is the college premium and lifetime wage-growth profiles oft-studied in the empirical literature. We make a simple point by contrasting the perspective afforded by cross-sectional data with that of cohort-based data: what we observe across ages at a point in time differs from what we see within a cohort over time, which argues in favor of a nonstationary framework to analyze wage inequality.[1]

Our review of the college premium and lifetime wage-growth profiles also allows us to emphasize rich dynamics in the data that we later exploit to estimate our theoretical model. The college premium – the wage gap between college and non-college workers – follows a non-monotonic trajectory over time: in what Autor et al. (2020) describe as a "real rollercoaster ride", it increased during the 1950s and 1960s, narrowed in the 1970s, and surged again after 1980. As for lifetime wage growth, prior research has documented a flattening of wages over the life cycle for the 1940 to 1970 cohorts. We highlight a reversal: expected lifetime wage growth became steeper for cohorts entering the labor market after 1970. This rebound is misrepresented in cross-sectional data – underestimated for skilled workers and overestimated for unskilled ones – presumably because such data fail to account for the changes in the macroeconomic environment and evolving cohort characteristics. Overall, the double dip in the college premium and the shifting profile of lifetime wage growth offer rich ground for identifying our nonstationary model.

A model of human capital. We then develop a general equilibrium OLG model of human capital à la Ben-Porath (1967), with three distinctive features. First, educational attainment is endogenous. Before entering the labor market, individuals choose whether to

[1] To illustrate the difference between cross-sectional and cohort-based views of wage inequality, consider the college premium as measured among older workers. A cross-sectional snapshot from 1980 shows that college-educated older workers earned, on average, 45% more than their non-college counterparts. However, this static comparison masks important dynamics. The cohort that entered the labor market in 1980 reached older age around 2010. By then, these same individuals – now older workers – were earning 75% more than their non-college peers.

attend college based on their expectations of future returns, which themselves depend on the college premium, i.e., the relative price of efficient labor units supplied by workers with different levels of educational attainment. Second, the model is cast in a general equilibrium framework, with a CES production function combining heterogeneous worker types. Hence the price of labor and thereby the college premium are endogenously determined. Third and crucially, our model incorporates several exogenous driving forces "dragging" the economy along a transition path. Specifically, the production function is subject to aggregate shocks that are either skill-neutral or skill-biased (i.e., SBTC) in nature, and successive cohorts entering the labor market may differ in terms of initial human capital endowments and learning capabilities.

Using U.S. Census data from 1940 to 2020, we structurally estimate all model parameters, including the time paths of aggregate and cohort-specific shocks. Through the estimation exercise, we also recover key unobserved quantities and prices such as the supply of efficient labor units from different educational groups and the price of labor.[2]

Results. We estimate an elasticity of substitution between skilled and unskilled workers around 2 and a time path of SBTC shocks that is highly consistent with the narrative of technological acceleration: a modest rise through the mid-century, followed by a sharp takeoff starting in the 1980s. These estimation results are valuable in their own right: the recent literature (reviewed below) has argued in favor of higher elasticity values, and uncovering such timing for SBTC has typically proved difficult.

The distinction between bodies – the number of skilled and unskilled workers – and efficient labor units – reflecting on-the-job human capital accumulation through the Ben-Porath technology – plays a pivotal role in these results. In particular, there is a positive spillover effect coming from the fact that workers tend to invest more in human capital accumulation relative to a scenario in which they would internalize the impact on the aggregate price of labor. This spillover effect amplifies the gap between bodies and efficient labor units. According to the model, the time path of relative efficient labor units picks up earlier than that of the relative supply of college versus non-college workers, explaining our estimation results for SBTC.[3] Our estimated CES elasticity around 2 also derives from this: college and non-college workers entering the aggregate production function are highly heterogeneous once we account for efficient labor units.

[2] The identification strategy exploits variation across both time and cohorts: we use the curvature of life-cycle wage profiles across cohorts to disentangle the price and quantity components of human capital.

[3] The model also predicts that, after the 2000s, while the quality of skilled cohorts stagnates, the quality of unskilled cohorts deteriorates more rapidly, causing the skilled/unskilled quality ratio to continue rising even as education rates level off.

The estimation exercise yields two other key results. First, it finds that the quality of recent cohorts of workers has deteriorated in terms of both initial human capital endowments – the human capital stocks they bring to the labor market upon entry – and learning capabilities – the TFP parameter of the Ben-Porath technology. Second, it shows that the relative aggregate price of labor (i.e., college versus non-college workers) has remained remarkably stable since 1940. Consequently, the dynamics of wage inequality are driven by changes in quantities: the supply of workers and efficient units of labor.

Finally, by conducting counterfactual scenarios, we disentangle the roles of aggregate and cohort-specific shocks as well as endogenous adjustment mechanisms in shaping wage inequality. We establish, first, that aggregate shocks, and in particular SBTC, are important to capture the dynamics of the college premium rollercoaster and shifting profile of lifetime wage growth, yet that cohort-specific changes in human capital parameters play an even more important role. Second, we find that suppressing two endogenous adjustment mechanisms, namely cohort-specific changes in educational attainment and changes in the aggregate skill prices, leads to a massive increase in wage inequality. For instance, without these forces, the college premium in 2020 would be between 3 and 3.5 vs. 1.9 in the data and baseline model. Hence the model highlights a somewhat overlooked lesson from general equilibrium analyses: that equilibrium adjustment can act as a mitigating force on wage inequality.

Related literature. Our paper contributes to a literature that employs structural models to analyze the determinants of the college premium and lifetime wage profiles.[4] In a nutshell, the novelty of our approach is to combine endogenous human capital accumulation, an educational choice margin, and a general equilibrium OLG setup, and estimate it along the transition path of the U.S. labor market between 1940 and 2020. This structure allows us to reproduce the college premium rollercoaster, the rebound of lifetime wage growth, along with the secular increase in college attainment, as the outcomes of forward-looking decisions and aggregate interactions.

A key paper in this literature is Heckman et al. (1998). The authors set up a rich general-equilibrium model with a Ben-Porath (1967) technology and prices of labor efficiency units derived from a CES production function for aggregate output which takes non-college and

[4] Our analysis contributes more broadly to the literature on U.S. wage inequality. This research, which is too voluminous to be reviewed here, has identified numerous drivers of wage inequality that we somehow seem to abstract from, including changes in the real value of the minimum wage (e.g., DiNardo et al. (1996), Lee (1999a)), the erosion of workers' bargaining power (e.g., Freeman (1992), Card (2001)), globalization and trade liberalization (e.g., Krugman (1995, 2008), Helpman (2018)), and taxation and top-end wage inequality (e.g. Piketty & Saez (2003)), to name a few. We are cognizant of these factors and we intend by no means to downplay their importance. These factors are partly encapsulated in the variable coined "skill-neutral technological change" in the model, which contributes to driving overall wage inequality. More importantly, and as mentioned above, the model explains only a portion of overall wage inequality.

college workers as its inputs. These are the key elements of our analysis as well, but our model is simplified compared to Heckman et al. (1998) as we abstract from savings decisions and physical capital.[5] These simplifications allow us to consider a larger set of exogenous driving forces (aggregate and cohort-specific shocks) together with endogenous changes in the education composition of the labor force. By putting these factors in competition against each other, we obtain a rich assessment of the sources of changes in U.S. wage inequality. Most notably, the educational choice margin plays a key role in our analysis, dampening the rise of the college premium.

The paper is also closely related to a key contribution by Guvenen & Kuruscu (2010). The authors develop a variant of Ben-Porath (1967), with linear utility as in our analysis, featuring several dimensions of worker heterogeneity that shape the response of the wage distribution to a SBTC shock. We view our analysis as complementary in that we abstract from heterogeneity in initial human capital endowments and learning capabilities within cohorts, while, on the other hand, we analyze how these have changed across successive cohorts.[6,7] Most importantly, unlike Guvenen & Kuruscu (2010), we allow non-college and college workers to be imperfect substitutes in the aggregate production function, and we let the educational composition adjust endogenously over time. As mentioned, general-equilibrium effects play a major role according to our estimated model.

Our paper also contributes to the literature on estimating the elasticity of substitution between skilled and unskilled workers, which is usually put at around 1.5 (see, among others, Katz & Murphy (1992), Heckman et al. (1998), Krusell et al. (2000), and Card & Lemieux (2001)). In contrast to Bowlus & Robinson (2012), who provide a decomposition with exogenous prices, and Bowlus et al. (2023), who identify prices from flat wage profiles and estimate a very high elasticity, our approach jointly endogenizes prices and quantities within a general equilibrium OLG framework. Bowlus et al. (2023) and Bils et al. (2025) revises this elasticity upward, estimating it at around 4. While — like these two papers — we distinguish between labor measured in efficiency units and in headcounts, our estimate of an elasticity of substitution of 2 remains more consistent with the conventional estimates. This allows us to capture both educational adjustment mechanisms and cohort quality dynamics, resulting in a more moderate elasticity and a richer explanation of the college premium.

[5] Consequently, we keep the real interest rate unchanged throughout the estimation and experiments.

[6] In addition, Guvenen & Kuruscu (2010) consider two types of labor, raw and abstract (with only the latter becoming more productive as workers acquire human capital), and also allow for worker heterogeneity in terms of human capital investment windows and beliefs. All these features are absent from our model.

[7] Guvenen & Kuruscu (2012) argue that the Ben-Porath model with only one type of labor cannot generate changes in wage inequality resulting from SBTC (Proposition 6 in their paper). However, their argument relies on SBTC being a one-off, surprise, permanent change in the productivity parameter that favors skilled workers, which is different from our analysis.

Outline. The paper is organized as follows. Section 2 presents stylized facts contrasting cross-sectional and cohort views of wage inequality. This sets the stage for our model presented in Section 3 and estimated in Section 4. That section also discusses mechanisms that explain wage inequality at a given point in time. In Section 5, we use counterfactual scenarios to analyze the dynamics of the college premium and lifetime wage growth. Section 6 concludes.

2 Stylized facts : Cross-section vs. cohort-based

In this section, we make a simple point. We consider the college premium and wage-experience profiles oft-studied in the empirical literature, but we contrast the perspective afforded by cross-sectional data with that of cohort-based data. As wage inequality statistics across ages at a point in time differ from those within a cohort over time, we argue in favor of a nonstationary framework.

Data on real weekly earnings by education and age. We use decennial IPUMS U.S. Census data from 1940 to 2020, focusing on full-time, full-year male wage earners aged 16 to 59 (as in Katz & Murphy (1992), Jeong et al. (2015) among others).[8] Workers are categorized as either "college" (some college education or more) or "non-college" (high school education or less). Throughout the paper, a cohort is defined by the year (decade) of labor market entry. The analysis begins with the 1940 cohort, as this is the first cohort for which U.S. Census earnings data are available. Notice that cohorts 1940 through 1990 are observed over their complete working lives, using data from 1940 to 2020. "Age" refers to years of work experience since labor market entry. Experience is calculated as the number of years since completing formal education and is grouped into four categories: 0-9 (referred to as "young"), 10-19, 20-29, and 30-39 years (referred to as "old"). All weekly earnings are adjusted to 2010 dollars using the Consumer Price Index. While the dataset consists of repeated cross-sections rather than panel data, it offers large, representative samples across time.

Table 1 displays the college premium and the experience premium across successive cohorts, using two distinct measurement strategies: cross-sectional versus cohort-based comparisons. Each entry reports the ratio of real weekly wages between groups (e.g., college vs. non-college, old vs. young), allowing us to contrast what one observes when comparing individuals at a point in time versus tracking cohorts over their working lives.

[8] To avoid distortions caused by the COVID-19 pandemic, we use 2019 data as our endpoint, hereafter referred to as "2020". See Appendix A for further details.

Table 1: College premium and experience premium: Cross-section vs. cohort

Cohort	College premium			Experience premium			
	Young	Old		College		Non-college	
		Cross-sec.	Cohort	Cross-sec.	Cohort	Cross-sec.	Cohort
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1940	1.62	1.60	1.56	1.63	3.17	1.66	3.30
1950	1.25	1.40	1.59	1.47	2.48	1.31	2.15
1960	1.43	1.56	1.57	1.50	1.88	1.38	1.71
1970	1.43	1.56	1.67	1.53	1.69	1.40	1.44
1980	1.37[(a)]	1.45[(b)]	1.75[(c)]	1.64[(d)]	1.88[(e)]	1.55	1.48
1990	1.58	1.57	1.90	1.72	1.96	1.73	1.63

NOTE: 'College premium': real weekly wage of college-educated workers relative to non-college workers. 'Experience premium': real weekly wage of older workers relative to young workers. 'Young': workers with 0-9 years of experience. 'Old': workers with 30-39 years of experience. 'Cross-section': ratios computed using young and old workers from the same year of cross-sectional data. 'Cohort': ratios computed using data from when the cohort was young and again when the same cohort was old (30 years later). [(a)] In 1980, young college workers earned 37% more than their non-college counterparts. [(b)] In 1980, old college-educated workers (those who entered the labor market in 1950) earn 45% more than their non-college counterparts (who had also entered the labor market in 1950)). [(c)] Old college-educated workers from the 1980 cohort (those who are "old" in 2010) earned 75% more than non-college old workers from the same cohort. [(d)] Old workers in 1980 earn 64% more than young workers that same year. [(e)] Old workers from the 1980 cohort (those who are "old" in 2010) earn 88% more than young workers from the same cohort (i.e., those entering the labor market in 1980).

College premium. Table 1, column (1) displays the evolution over time of young workers' college premium. One can clearly see the "rollercoaster ride" (Autor et al. (2020)) : the college wage premium rebounded in the 1950s and 1960s before narrowing in the 1970s, and then greatly increasing post-1980. A similar pattern is observed for older workers.

Let us now compare the "cross-sectional view" and "cohort-based view" of the college premium. In 1980, using cross-sectional data, college-educated older workers earned, on average, 45% more than their non-college counterparts (column (2)). In contrast, the cohort that entered the labor market in 1980 reached older age around 2010. In that year, older workers from the 1980 cohort earned 75% more than their non-college peers (column (3)). This discrepancy arises presumably because the 1980 cohort benefited from the rising SBTC over the course of its lifetime – an effect that is naturally missed by the cross-sectional view relying on a snapshot of data in 1980.

Experience premium: wage flattening/wage steepening. A similar pattern emerges with the experience premium (also referred to as "age premium", "lifetime wage profile", or "expected lifetime wage growth").[9]

Focusing on college-educated workers, column (5) reports the cohort-based experience premium, the wage of older workers relative to young workers from the same cohort. For the 1940 cohort, whose working life spanned from 1940 to 1970, this premium is 3.17, indicating that wages more than tripled over their working life. In contrast, the cross-sectional experience premium observed in 1940 (column (4)) is only 1.63. This discrepancy arises presumably because the cohort-based measure captures the post-World War II economic boom that shaped the careers of the 1940 cohort. Such macroeconomic dynamics are entirely missed when comparing young and old workers *within the same cross-sectional data* in 1940. Our model explicitly incorporates these changes in aggregate conditions when simulating life-cycle earnings profiles.

In addition, notice in column (5) that expected wage growth drops for later cohorts: 2.48 for the 1950 cohort, down to 1.69 for the 1970 cohort, consistent with what the literature refers to as "wage flattening". Including more recent data provides us with some new insights. For the 1980 and 1990 cohorts, we observe "wage steepening": cohort-based experience premia are 1.88 and 1.96 (column (5)), respectively. These patterns suggest a rebound of lifetime wage growth for recent cohorts of college-educated workers. This is consistent with the gradual unfolding of SBTC, which continues to raise the relative demand for skilled labor – not only benefiting young workers entering the labor market, but also older workers progressing through their careers.

Crucially, these dynamics are missed when looking only at cross-sectional data. [10] Comparing columns (4) and (5) of Table 1, we observe that the cross-sectional view tends to underestimate lifetime wage growth for college-educated workers from the 1970 cohort onward. Symmetrically, as we expect SBTC to depress the wages of non-college workers, cross-sectional data (columns (6) and (7)) tend to overestimate their life-cycle wage growth over the same period.

In sum, Table 1 illustrates the contrast between cross-sectional and cohort-based views of wage inequality: what we observe across ages at a point in time differs from what we see within a cohort over time. This contrast itself indicates changes in the underlying macroeconomic environment, which underpins the theoretical framework we develop in the rest of the

[9] Previous studies provide some explanations about lifetime wage inequality (Huggett et al. (2011)). One factor is changes in the returns to skills, as well as changes in professional mobility, as suggested by Kambourov & Manovskii (2009) and changes in the remuneration of individual skills, as highlighted by Lagakos et al. (2018). Furthermore, demographic changes in the workforce have also been linked to this phenomenon, as suggested by Jeong et al. (2015), Hendricks (2018) and Kong et al. (2018).

[10] This echoes recent evidence by Kleven et al. (2025), who show that short-run micro estimates of labor supply elasticities typically close to 0.2 substantially understate long-run responses, around 0.5, once dynamic career mechanisms such as promotions and job switches are taken into account.

paper. At the same time, the cross-sectional and cohort-based profiles of wage inequality are intimately related in that all age groups working within the same year face the same rental price for their human capital during that year. This aspect will be at the core of our model's estimation.

3 Model

3.1 Overlapping cohorts

The economy is populated by overlapping cohorts of workers. A cohort is indexed by c, which denotes the decade when it enters the labor market. A cohort is a continuum of workers whose age is indexed by a. Age is discretized into four intervals which, equivalently, refer to the number of years of work experience, namely 0-9, 10-19, 20-29 and 30-39 years.[11] Although somewhat of misnomers, we will refer to "young" or "early career" individuals those with 0-9 years of work experience, and "old" or "late-career" individuals those in the 30-39 interval. Hence, $a \in [0, 10, 20, 30]$, while $c \in [1910, 1920, ..., 2020]$ tracks the decade of entry into the labor market. Age and cohort are related to time (decades) through $t = a + c$.

There are two education groups, indexed by z. Before entering the labor market, young workers choose whether or not to pursue higher education. Those who attend college are referred to as "skilled" workers ($z = s$), while those who do not are considered "unskilled" workers ($z = u$). Although the share of c-cohort educated workers L^s_c is determined endogenously within the model, the age distribution for each skill group z is calibrated exogenously using census data. In any given year t, four age groups a overlap in the labor market and hence in the production function. Let $\Pi^z_{c,t}$ denote the share of workers of age $a = t - c$ (i.e., belonging to cohort c) and skill level z. The total population of workers in the labor market is normalized to 1 at any time t, such that $\sum_{a,z} \Pi^z_{t-a,t} = 1$.[12]

[11] As the model is calibrated on decennial Census data, we consider 10-year intervals.

[12] Let M_c denote the mass of new entrants and L^s_c the fraction of skilled workers of type s within cohort c. The mass of skilled entrants at date t (the birth year of cohort c) is therefore $M^s_{t,t} = L^s_t M_t$, i.e., a share $\Pi^s_{t,t} \equiv \frac{M^s_{t,t}}{M_t} = L^s_t$ of that new population. The population mass evolves according to: $M^z_{t,t+a} = (1-\varrho^z_{t,t+a})M^z_{t,t+a-10}$, $\forall a \in \{10, 20, 30\}$, and $\forall z \in \{s, u\}$, where $\varrho^z_{t,t+a}$ is the net-exit rate (i.e., the effect of mortality and migration). The share of skilled workers in that cohort reaching experience level a is then $\frac{M^z_{t,t+a}}{M_t} = L^z_t \prod^a_{i=10}(1 - \varrho^z_{t,t+i})$. By definition $\Pi^s_{t,t+a} = \frac{M^z_{t,t+a}}{M_{t+a}}$, so that $\frac{M^z_{t,t+a}}{M_t} = \Pi^z_{t,t+a} \frac{M_{t+a}}{M_t}$. Hence, $\Pi^s_{t,t+a} = \frac{M_t}{M_{t+a}} L^z_t \prod^a_{i=10}(1 - \varrho^z_{t,t+i})$ links the demographic weights at each date ($\Pi^s_{t,t+30}$) to the endogenous skill choice L^s_t. More concisely, $\Pi^s_{t,t+30} = \chi^s_{t,t+30} L^s_t$, where $\chi^s_{t,t+30} \equiv \prod^{30}_{i=10}(1 - \varrho^z_{t,t+i})$ is exogenous and observed in the data, allowing us to construct the macroeconomic aggregates of the model using the observed $\Pi^z_{t,t+a}$.

3.2 Human capital investments

Schooling choice. Choices about education are made once and for before entering the labor market. Workers are heterogeneous with respect to their costs of enrolling in college education. These costs, which capture both the monetary and nonpecuniary components of the decision, are idiosyncratic shocks ε drawn from a random distribution $\mathcal{G}$. Workers observe the realization of ε and choose whether to attend college before age $a = 0$ by solving:

$$\max\{V_c^u; V_c^s - \varepsilon\},$$

where V_c^z, $z \in \{s, u\}$, is the expected discounted sum of wages for workers from cohort c (hence entering the labor market in year $t = c$) with education level z. Since schooling is a binary decision and the idiosyncratic cost ε is sunk once that decision is made, a worker enrolls in college education and becomes "skilled" ($z = s$) when $\varepsilon \leq \widetilde{\varepsilon}_c$, where $\widetilde{\varepsilon}_c = V_c^s - V_c^u$. Thus, the share of college workers from cohort c is:

$$L_c^s = \mathcal{G}(\widetilde{\varepsilon}_c) = \mathcal{G}(V_c^s - V_c^u) \tag{1}$$

On-the-job training (OJT). In each period of her working lifetime (i.e., $a \in [0, 10, 20, 30]$), a worker of skill level z has one unit of time that can be allocated to working and investing in human capital accumulation through OJT. As time devoted to OJT is diverted from working, the cost of human capital accumulation is measured in terms of foregone wages. A worker from cohort c enters the labor market at time $t = c$ without any experience, i.e. $a = 0$, and works until age $a = 30$, i.e. retires at time $t = c + 30$. Her objective is:

$$V_c^z = \max_{e_{a,c}^z \in [0;1]} \sum_{a=0}^{30} \beta^a y_{c+a}^z \quad s.t. \quad \begin{cases} y_{c+a}^z &= \ell_{a,c}^z R_t^z \\ \ell_{a,c}^z &= (1 - e_{a,c}^z) h_{a,c}^z \\ h_{a+10,c}^z &= (1-\delta) h_{a,c}^z + \alpha_c^z (e_{a,c}^z h_{a,c}^z)^{\zeta^z} \end{cases} \quad \forall z = s, u. \tag{2}$$

β is the discount factor. y_{c+a}^z denotes the real wage of a worker with skill z at time $t = c + a$. The wage is the product of the worker's individual units of efficient labor $\ell_{a,c}^z$ and the aggregate rental price of human capital R_t^z (also referred to as the "price of labor" or "skill price") during year t for skill level z. Efficient labor $\ell_{a,c}^z$ depends on two elements: first, the stock of human capital $h_{a,c}^z$ and, second, time devoted to OJT, denoted as $e_{a,c}^z$. The dynamics of the human capital, starting from the initial (cohort-specific) endowment $h_{0,c}^z$, accounts for depreciation over time at rate δ, and workers' human capital investment through OJT. Importantly, note that in (2) the curvature of the production function of human capital ζ^z is assumed to be skill-specific, while the initial human capital endowment and the ability-to-learn parameter $\{h^z_{0,c}; \alpha^z_c\}$ are both skill- and cohort-specific.

The Ben-Porath (1967) model admits an analytical solution (see Huggett et al. (2011)) for a given sequence of skill prices that a worker faces over her working lifetime, $\{R^z_a\}^{30}_{a=0}$, $z \in \{s, u\}$. Let us define $\Omega^z_{a,c} \equiv \frac{(e^z_{a,c} h^z_{a,c})^{1-\zeta^z}}{\alpha^z_c \zeta^z}$, for which the solution is determined by[13]

$$\Omega^z_{a,c} = \beta \frac{R^z_{t+10}}{R^z_t} \left[1 + (1-\delta)\Omega^z_{a+10,c}\right] \quad \text{with} \quad \Omega^z_{30,c} = 0, \quad t = a + c. \tag{3}$$

Time optimally allocated to OJT and the dynamics of human capital dynamics are:

$$e^z_{a,c} = \frac{(\alpha^z_c \zeta^z \Omega^z_{a,c})^{\frac{1}{1-\zeta^z}}}{h^z_{a,c}}, \tag{4}$$

$$h^z_{a+10,c} = (1-\delta) h^z_{a,c} + (\alpha^z_c)^{\frac{1}{1-\zeta^z}} (\zeta^z \Omega^z_{a,c})^{\frac{\zeta^z}{1-\zeta^z}}, \tag{5}$$

given $h^z_{0,c}$, the initial stock of human capital for workers from cohort c and education level z. The recursive solution to the Ben-Porath problem delivers a set of supply functions for efficient units of labor, $\ell^z_{a,c} \equiv (1 - e^z_{a,c}) h^z_{a,c}$ with $c = t - a$, given by:

$$\begin{aligned} \ell^z_{30,t-30} &= \Lambda(R^z_{t-30}, R^z_{t-20}, R^z_{t-10}, R^z_t) \\ \ell^z_{20,t-20} &= \Lambda(R^z_{t-20}, R^z_{t-10}, R^z_t, R^z_{t+10}) \\ \ell^z_{10,t-10} &= \Lambda(R^z_{t-10}, R^z_t, R^z_{t+10}, R^z_{t+20}) \\ \ell^z_{0,t} &= \Lambda(R^z_t, R^z_{t+10}, R^z_{t+20}, R^z_{t+30}), \end{aligned} \tag{6}$$

$z \in \{s, u\}$. The functions $\Lambda(\cdot)$ highlight that the efficient labor supply decisions depend on the entire path of skill prices R^z_t over an individual's lifetime.

3.3 Aggregate output

In the goods market, output is produced by a perfectly competitive firm according to:

$$Y_t = X_t F(\mathcal{L}^u_t, \mathcal{L}^s_t) = X_t \left[(\mathcal{L}^u_t)^\eta + d_t (\mathcal{L}^s_t)^\eta \right]^{\frac{1}{\eta}} \quad \text{with} \quad \begin{cases} \mathcal{L}^u_t = \sum_c \ell^u_{t-c,c} L^u_c \chi^u_{c,t} \\ \mathcal{L}^s_t = \sum_c \ell^s_{t-c,c} L^s_c \chi^s_{c,t}, \end{cases} \tag{7}$$

and $\eta \in (-\infty; 1[$. In (7), the inputs $\mathcal{L}^z_t$, $z \in \{s, u\}$, represent aggregate units of efficient labor at time t. $\frac{1}{1-\eta}$ is the elasticity of substitution between skilled and unskilled labor – a key parameter in our analysis.[14] X_t is a common shifter capturing labor-augmenting technolog-

[13] See Appendix B for details and analytical proofs.

[14] Labor is aggregated within each skill group by summing over all age groups, meaning that workers of different ages are perfect substitutes within skill groups. However, note that workers from different age

ical change, but also potentially other evolving features of the macroeconomic environment such as labor market institutions.[15] For simplicity, we refer to the shock process X_t as skill-neutral technological change. In contrast, d_t embodies skill-biased technological change (SBTC hereafter). Note that the shocks captured by X_t and d_t are truly aggregate shocks, as they affect all workers present in the labor market at time t. Finally, the production function in (7) abstract from physical capital.

Recall that each worker supply $\ell^z_{a,c} = (1-e^z_{a,c})h^z_{a,c}$ units of efficient labor, made up of time spent working on the job $(1-e^z_{a,c})$ and human capital $(h^z_{a,c})$. The aggregate input $\mathcal{L}^z_t$ is the sum of all efficient labor units $\ell^z_{t-c,c}$ offered by all cohorts working in period t, weighted by demographic composition: $\Pi^z_{c,t} = L^u_c \chi^z_{c,t}$. Finally, note that in our human capital framework, a clear distinction is made between the total supply of labor of type z in year t, denoted L^z_t, and its effective use in the production function, denoted $\mathcal{L}^z_t$. The latter adjusts the raw labor supply by labor quality, which is determined by efficiency levels, ultimately governed by the accumulation of human capital. Investment in human capital creates the wedge between the two measures of human capital stock L^z_t and $\mathcal{L}^z_t$. Wages $y^z_{a,c}$ are given by:

$$\begin{aligned} y^u_{a,c} &= \frac{\partial Y_t}{\partial \mathcal{L}^u_c} = \ell^u_{a,c} X_t F_{u,t} = \ell^u_{a,c} X_t \left(\mathcal{L}^u_t\right)^{\eta-1} \left[\left(\mathcal{L}^u_t\right)^{\eta} + d_t \left(\mathcal{L}^s_t\right)^{\eta} \right]^{\frac{1}{\eta}-1} \equiv \ell^u_{a,c} R^u_t \\ y^s_{a,c} &= \frac{\partial Y_t}{\partial \mathcal{L}^s_c} = \ell^s_{a,c} X_t F_{s,t} = \ell^s_{a,c} X_t d_t \left(\mathcal{L}^s_t\right)^{\eta-1} \left[\left(\mathcal{L}^u_t\right)^{\eta} + d_t \left(\mathcal{L}^s_t\right)^{\eta} \right]^{\frac{1}{\eta}-1} \equiv \ell^s_{a,c} R^s_t \end{aligned} \tag{8}$$

where $y^z_{a,c}$ is observed in the data as the average real weekly wage of workers of age a from cohort c and skill level z. Workers' efficient labor, $\ell^z_{a,c}$, and the aggregate price of skill z at time t, R^z_t, are endogenously determined in the model. The path of skill prices R^z_t depends directly on the paths of the aggregate shocks $\{X_t, d_t\}$, and indirectly through the endogenous adjustments of $\ell^z_{c,t}$ coming from individuals' responses to changes in skill prices.

groups belong to distinct cohorts that differ in initial human capital endowments $h^z_{0,c}$ and learning ability α^z_c. Consequently, the aggregation combines heterogeneous types of labor for which quality is pre-determined, reducing the degree of substitutability between age groups within a skills z.

[15] As an illustration, consider how a change in the legal minimum wage, denoted as w^M_t, would affect the model's equilibrium. With a uniform productivity distribution $\epsilon \sim \mathcal{U}[\underline{\epsilon}, \overline{\epsilon}]$ among unskilled workers and an aggregate unskilled employment given by $\mathcal{L}^u_t = \sum_a \int_{\epsilon^*}^{\overline{\epsilon}} \epsilon(i) \ell^u_{a,t-a} L^u_{t-a} \chi^u_{t-a} di$, the average wage for unskilled workers is given by $\overline{R}^u_t = \frac{1}{2}(\overline{\epsilon} R^u_t + w^M_t)$. Indeed, the real wage of individual i is $R^u_t(i) = \max\{w^M_t, \epsilon(i) R^u_t\}$ with $\epsilon(i) R^u_t$ the marginal productivity of each worker i where $R^u_t = X_t \left(\mathcal{L}^u_t\right)^{\eta-1} \left[\left(\mathcal{L}^u_t\right)^{\eta} + d_t \left(\mathcal{L}^s_t\right)^{\eta}\right]^{\frac{1}{\eta}-1}$. The worker is employed only if $\epsilon(i) R^u_t \geq w^M_t$, i.e., $\epsilon(i) \geq \epsilon^*_t := \frac{w^M_t}{R^u_t}$. In this case, the average wage for unskilled workers is $\overline{R}^u_t = R^u_t \frac{\overline{\epsilon} + \epsilon^*_t}{2}$. Hence, a change in w^M_t would affect $\overline{R}^u_t$ just like any other shock captured by X_t.

3.4 Equilibrium properties

We now examine key properties of the model to gain insights into the mechanisms driving movements in the college premium and changes in lifetime wage growth.

GE spillovers of human capital investments. The model naturally incorporates general equilibrium spillover effects from human capital investment decisions. Indeed, from (6) and (8), we can rewrite the model's solution as

$$\left.\begin{array}{rcl} y^z_{30,t-30} &=& \ell^z_{30,t-30}R^z_t \\ y^z_{20,t-20} &=& \ell^z_{20,t-20}R^z_t \\ y^z_{10,t-10} &=& \ell^z_{10,t-10}R^z_t \\ y^z_{0,t} &=& \ell^z_{0,t}R^z_t \end{array}\right\} \Leftrightarrow \left\{\begin{array}{rcl} y^z_{30,t-30} &=& \Phi(R^z_{t-30}, R^z_{t-20}, R^z_{t-10}, R^z_t) \\ y^z_{20,t-20} &=& \Phi(R^z_{t-20}, R^z_{c-10}, R^z_t, R^z_{t+10}) \\ y^z_{10,t-10} &=& \Phi(R^z_{t-10}, R^z_t, R^z_{t+10}, R^z_{t+20}) \\ y^z_{0,t} &=& \Phi(R^z_t, R^z_{t+10}, R^z_{t+20}, R^z_{t+30}) \end{array}\right. \tag{9}$$

where $\Phi(\cdot) = \Lambda(\cdot)R^z_t$. Property 1 clarifies these relations by highlighting the sources of wage changes:

Property 1. *In response to aggregate shocks to either X_t or d_t, the wage $y^z_{a,c}$ of a-c-z individuals grows if workers raise their supply of efficient labor $\ell^z_{a,c}$ and/or the rental price of human capital R^z_t increases. These two drivers of wage changes are intertwined because:*

- *(i) OJT increases when workers anticipate growth in the price of human capital R^z_t, which they take as given (Equation (3));*
- *(ii) R^z_t decreases (through marginal productivity effects) with $\mathcal{L}^z_t$, the aggregate units of efficient labor entering production at time t (Equation (8)).*

Points *(i)* and *(ii)* in Property 1 give rise to a positive spillover effect in the model. Individuals choose their OJT based on the expected path of R^z_t, which they take as given. As a result, workers ignore two key effects: (a) their own OJT actually influence the aggregate price R^z_t; and (b) the OJT efforts of others increase overall productivity and wage gain. As a result, workers tend to invest more in OJT relative to a scenario in which they would internalize these positive spillovers.

College premium. The average wage for each skill level $z \in \{s, u\}$ is given by

$$Y^z_t = \frac{R^z_t \sum_a \ell^z_{a,t-a} L^z_{t-a} \chi^z_{t-a}}{\sum_a L^z_{t-a} \chi^z_{t-a}} = R^z_t \frac{\mathcal{L}^z_t}{L^z_t}. \tag{10}$$

Hence, the average depends on the price of labor R^z_t and the aggregate stock of efficient units of labor $\mathcal{L}^z_t$ normalized by the population size L^z_t of z-skilled workers at time t. $\mathcal{L}^z_t$ aggregates the individual human-capital investment decisions from all age groups within year t (which are affected by the aggregate price of labor R_t^z). L_t^z depends on the educational choices of each successive cohort (also affected by the aggregate price of labor R_t^z).

Property 2. *The college premium, given by*

$$\frac{Y_t^s}{Y_t^u} = \frac{R_t^s}{R_t^u}\frac{\frac{\sum_a \ell_{a,t-a}^s L_{t-a}^s \chi_{t-a}^z}{\sum_a L_{t-a}^s \chi_{t-a}^s}}{\frac{\sum_a \ell_{a,t-a}^u L_{t-a}^u \chi_{t-a}^u}{\sum_a L_{t-a}^u \chi_{t-a}^u}} = d_t \left(\frac{\mathcal{L}_t^s}{\mathcal{L}_t^u}\right)^{\eta} \frac{1-L_t^s}{L_t^s} \tag{11}$$

depends on the SBTC shifter d_t, educational choices through L_t^z, $z \in \{s,u\}$, and the aggregate efficient labor inputs of each skill group $\mathcal{L}_t^z$, $z \in \{s,u\}$.

By applying logs to Equation (11), we can clearly express a relation between our model and the college premium literature. We have:

$$\log\left(\frac{Y_t^s}{Y_t^u}\right) = \underbrace{\log(d_t)}_{\text{SBTC}} + \eta \underbrace{\log\left(\frac{\mathcal{L}_t^s}{\mathcal{L}_t^u}\right)}_{\substack{\text{efficient}\\ \text{labor units}}} - \underbrace{\log\left(\frac{L_t^s}{1-L_t^s}\right)}_{\text{skill supply}} \tag{12}$$

The first element of (12), SBTC, increases the demand for skilled labor, thereby raising the college premium. The third component, the supply of skilled labor, mitigates the increase in the college premium. The middle component, efficient labor units, is a distinctive feature of our analysis. For instance, in Goldin & Katz (2007) and Acemoglu & Autor (2011), there is no distinction between bodies and efficient labor units, so that Equation (11) boils down to

$$\log\left(\frac{Y_t^s}{Y_t^u}\right) = \underbrace{\log(d_t)}_{\text{SBTC}} - \frac{1}{\epsilon} \underbrace{\log\left(\frac{L_t^s}{1-L_t^s}\right)}_{\text{skill supply}} \tag{13}$$

where $\epsilon = \frac{1}{1-\eta} > 0$ is the CES elasticity of substitution between skilled and unskilled labor. In our framework, the skill supply L_t^z is endogenous and may differ from efficient labor units $\mathcal{L}_t^z$. In this respect, our model cautions against running a simple OLS regression of log-relative wages against a time trend and the log skill supply in (13) to recover ϵ. As suggested by (12), this OLS regression would be fraught with endogeneity issues.

Steady-state environment versus transitional dynamics. In a non-stationary setting like ours (and in the observed data), the ratio of education premia across experience groups does not approximate differences in wage profiles across skill groups. Specifically, the ratio of the life-cycle wage profile of skilled to unskilled workers differs from the ratio of higher-education premia between age groups: $\frac{w^s_{30-39}/w^s_{0-9}}{w^u_{30-39}/w^u_{0-9}} \neq \frac{w^s_{30-39}/w^u_{30-39}}{w^s_{0-9}/w^u_{0-9}}$. This equivalence holds only in a stationary environment, where the cohort wage profiles and cross-sectional wage profiles coincide with each other (as in e.g. Jeong et al. (2015)).

4 Structural estimation

In this section, we describe how the parameters of the model are structurally estimated using wage and education U.S. Census data for all cohorts between 1940 to 2020. The estimation strategy leverages the model's OLG structure, cohort heterogeneity, and general equilibrium feedback mechanisms to jointly identify the key parameters governing individual behavior and macroeconomic outcomes. We then present and discuss several key estimation results.

4.1 Estimation strategy

Table 2 presents the U.S. Census wage data that we use to estimate the model.[16] As explained further below, we also use U.S. Census data describing the share of college-educated workers entering the labor market in $t = 1940, ..., 2020$.

Table 2: Observed wages across cohorts and over time

a															
30				y_{1940}	y_{1950}	y_{1960}	y_{1970}	y_{1980}	y_{1990}	y_{2000}	y_{2010}	y_{2020}	y	y	y
20			y	y_{1940}	y_{1950}	y_{1960}	y_{1970}	y_{1980}	y_{1990}	y_{2000}	y_{2010}	y_{2020}	y	y	
10		y	y	y_{1940}	y_{1950}	y_{1960}	y_{1970}	y_{1980}	y_{1990}	y_{2000}	y_{2010}	y_{2020}	y		
0	y	y	y	y_{1940}	y_{1950}	y_{1960}	y_{1970}	y_{1980}	y_{1990}	y_{2000}	y_{2010}	y_{2020}			
t	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000	2010	2020	2030	2040	2050

NOTE: t: year. a: age group. "0": 0-9 years of work experience. "10": 10 to 19 years of work experience. "20": 20 to 29 years of work experience. "30": 30 to 39 years of work experience. Each color denotes a cohort c aging over the years. Each cell y_t refers to wages for workers of age a observed in year t. The cohort c is given by $c = t - a$.

As an illustration, consider the *1980 cohort* in Table 2. These workers enter the labor market in 1980 at age $a = 0$, corresponding to 0-9 years of work experience. Ten years later, in 1990, they are observed with 10-19 years of experience ($a = 10$), and so on, up to the year 2010, when they reach 30-39 years of experience ($a = 30$). Thus, each cohort is observed over a span of four decades. Consider now the *year 1980* in Table 2. The labor market includes four cohorts in 1980: the 1950 cohort (age 30), the 1960 cohort (age 20), the 1970 cohort

[16] Note that for "old" workers in 1940, i.e. those from the 1910 cohort, we do not observe any prior wage. Similarly, we miss wage data on the 1920 and 1930 cohorts before 1940; these are the wages without a time subscript in Table 2. Likewise, in 2020, we miss information about the future: young workers in 2020 choose their life-cycle human capital conditional on their expectations on the future path of skill prices, up until 2050. We describe in this section how we infer these missing wages.

(age 10), and the 1980 cohort (age 0). The workers belonging to these four age groups face the *same* equilibrium skill price R^z_{1980}, which aggregates their heterogeneous productivity and investment decisions. This overlapping structure ensures that prices and behaviors are jointly determined: The aggregate prices affect the workers belonging to 4 successive 10-year cohorts within a given year (decade) while a given cohort makes decisions over a 40-year period. This enables the identification strategy described below.

Unknown parameters. The model period is set to be a decade. We calibrate $\beta = \frac{1}{(1.04)^{10}}$ to match an annual real interest rate of 4%. As in Heckman et al. (1998), we assume that δ is homogeneous across skill levels and cohorts. We let the curvature of the human production functions ζ^u and ζ^s be specific to each skill, but we restrict it to be homogeneous across cohorts. Last, we assume that $\mathcal{G}(\varepsilon)$ is log-normal, with mean μ_ε and standard deviation σ_ε. Given β, the vector $\Theta = \{\Theta_y, \Theta_s, \Theta_f\}$ of unknown parameters is defined by:

$$\Theta_y = \left\{ \left\{ \{\alpha^z_c, h^z_{0,c}\}^{2020}_{c=1910}, \{R^z_t\}^{2050}_{t=1910}, \zeta^z \right\}^{s}_{z=u}, \delta \right\} \quad \Theta_s = \{\mu_\varepsilon, \sigma_\varepsilon\} \quad \Theta_f = \left\{\eta, \{d_t, X_t\}^{2020}_{t=1940}\right\}$$

Θ_y consists of parameters and prices that regulate the OJT decision problems, with $dim(\Theta_y) = (2 \times 12 + 15 + 1) \times 2 + 1 = 81$.[17] Θ_s is the vector of parameters governing the schooling choice problem, with $dim(\Theta_s) = 2$. Θ_f contains parameters of the aggregate production function, with $dim(\Theta_f) = 1 + (2 \times 9) = 19$. Thus, the estimation of Θ requires at least $dim(\Theta) = 81 + 2 + 19 = 102$ moments from the data.

Empirical moments. Using U.S. Census data, we compute average wages $y^z_{c,t}$ by age a for the two skill levels $z \in \{s, u\}$ across six cohorts $c = \{1940, 1950, \ldots, 1990\}$ for which the data cover the full working life of workers (see Table 2). This yields 48 empirical moments (6 cohorts $\times$ 4 age groups $\times$ 2 skill levels).

For cohorts that entered the labor market before 1940 (1910, 1920, 1930) and cohorts that entered after 1990 (2000, 2010, 2020), part of the wage data is missing (see Table 2). To address this limitation, we construct fitted wage profiles to recover the complete lifetime wage profiles of the workers belonging to those cohorts.[18] This procedure yields 48 additional

[17]Note that the vector for R^z_t spans the years 1910 through 2050, whereas those for α^z_c and $h^z_{0,c}$ span years only until 2020. The reason is that the estimation seeks to rationalize data for "old" workers in 2020 ($y^z_{30,2020}$), among other data. Yet $y^z_{30,2020}$ depends on *all* workers that are present in the labor market at $t = 2020$, including the younger ones whose decisions depend on aggregate skill prices up until $2020 + 30 = 2050$.

[18]Appendix C describes how the out-of-sample data are estimated. For the wage profiles of the 1910 to 1930 cohorts, we verify the plausibility of the fitted profiles by comparing them to data from the 1915 Iowa State Census. For those of 2000, 2010, and 2020 cohorts, we cannot cross-check the fitted wage profiles against external data. Appendix C also details the additional restrictions required to estimate the general-equilibrium model over the period 1930–2020.

empirical moments.

The other key empirical moment is the share of skilled workers across cohorts, also derived from U.S. Census data. Specifically, we obtain 9 empirical moments, denoted L^s_c, where $c = \{1940, 1950, \ldots, 2020\}$, measuring the proportion of college-educated individuals among workers with 0 to 9 years of labor market experience.

The complete set of empirical targets is:

$$\psi = \left\{ \left\{ \{y^u_{a,c}\}_{a=0}^{30} \right\}_{c=1910}^{2020} ; \left\{ \{y^s_{a,c}\}_{a=0}^{30} \right\}_{c=1910}^{2020} ; \{L^s_c\}_{c=1940}^{2020} \right\} \quad \text{with } dim(\psi) = 105.$$

Given that $dim(\psi) > dim(\Theta)$, the model is over-identified and an estimate of Θ can be found by minimizing the distance $||\psi - m(\Theta)||$, where $m(\Theta)$ denotes the counterparts to the empirical moments contained in ψ generated (simulated) using the vector of model parameters Θ.

Intuition behind the identification of Θ_y. Using Equation (9) and a cross-section of U.S. Census wages $\{y^z_{a,t-a}\}_{a=0}^{30}$, the identification of the parameters is based on:

$$\begin{cases} y^z_{30,t-30} &= \Phi(R^z_{t-30}, R^z_{t-20}, R^z_{t-10}, R^z_t) \\ y^z_{20,t-20} &= \Phi(R^z_{t-20}, R^z_{c-10}, R^z_t, R^z_{t+10}) \\ y^z_{10,t-10} &= \Phi(R^z_{t-10}, R^z_t, R^z_{t+10}, R^z_{c+20}) \\ y^z_{0,t} &= \Phi(R^z_t, R^z_{t+10}, R^z_{t+20}, R^z_{c+30}) \end{cases} \quad \text{and} \quad \begin{cases} y^z_{30,t-20} &= \Phi(R^z_{t-20}, R^z_{t-10}, R^z_t, R^z_{t+10}) \\ y^z_{20,t-10} &= \Phi(R^z_{t-10}, R^z_t, R^z_{t+10}, R^z_{c+20}) \\ y^z_{10,t} &= \Phi(R^z_t, R^z_{t+10}, R^z_{t+20}, R^z_{c+30}) \\ y^z_{0,t+10} &= \Phi(R^z_{t+10}, R^z_{t+20}, R^z_{t+30}, R^z_{c+40}) \end{cases} \tag{14}$$

for each period $t = 1940, \ldots, 2010$ and skill group $z \in \{s, u\}$. Suppose that past skill prices R^z_{t-30}, R^z_{t-20}, and R^z_{t-10} are known (i.e., the R^z_{t-h} values on a white background). The top line of the left block of Equation (14) shows that R^z_t can be recovered directly from the wage and the optimal decisions of older workers (those with $a = 30$ at date t; gray background). Next, conditional on workers' optimal decisions, the remaining lines on the left allow us to back out the forward-looking prices R^z_{t+10}, R^z_{t+20}, and R^z_{t+30} (light-gray background). Moving to the next U.S. Census wave (the block on the right-hand side for period $t+10$ in (14)) adds four additional data moments $\{y^z_{a,t+10-a}\}_{a=0}^{30}$ – the cross-section of wage data for that period – but only one additional unknown, R^z_{t+40} (the sole value on a dark-gray background).

More generally, 4 skills prices $\{R^z_\tau\}_{\tau=t}^{t+30}$ can be derived from the time-t cross-section (given an initial vector $\{R^z_{t-30}, R^z_{t-20}, R^z_{t-10}\}$ and the model solution Φ), which implies that $\mathcal{C}$ cross-sections of wages provide us with $(\mathcal{C} - 1) \times (4 - 1)$ extra data moments. We use these additional free moments to identify $\left\{\alpha^z_c, h^z_{0,c}\right\}_{c=1940}^{2020}$ which are intuitively related to the level and slope of each cohort's lifetime wage profile. This dimension of the estimation process leverages the fact that the pooled U.S. Census data tracks cohorts over time – as opposed to exploiting the overlap between cohorts at a given point in time. It also allows us to recover the depreciation rate, δ.

Intuition behind the identification of Θ_f. For a given set of parameter estimates $\{\Theta_y, \Theta_s\}$, solving workers' decision problem yields values for:

$$\left\{\left\{\{L^z_{c,0}, y^z_{a,c}, \ell^z_{a,c}\}_{c=1910}^{2020}\right\}_{a=0}^{30}, \{R^z_t\}_{t=1910}^{2050}\right\}_{z=u,s} \quad \text{with} \quad \ell^z_{a,c} = (1 - e^z_{a,c})h^z_{a,c}.$$

By aggregating using population shares from U.S. Census data for each age and year, $\Pi^z_{a,t}$, we obtain the aggregate efficient labor inputs $\mathcal{L}^z_t$, $z \in \{s, u\}$ in the production function (Equation (7)) for each $t = 1940, ..., 2020$. Our approach to recover the elasticity of substitution between unskilled and skilled labor (η) follows Acemoglu & Autor (2011), albeit with a key difference. We rely on a time-series OLS estimation, as in Acemoglu & Autor (2011), but distinguish between the number of bodies, L^z_t, and the efficient units of labor $\mathcal{L}^z_t$. Specifically, given our model solution for the college premium ($\frac{Y^s_t}{Y^u_t}$) (see Equation (12)), we estimate

$$\underbrace{\log\left(\frac{Y^s_t}{Y^u_t}\right) + \log\left(\frac{L^s_t}{1 - L^s_t}\right)}_{\text{dependent variable}} = g(t) + \eta \log\left(\frac{\mathcal{L}^s_t}{\mathcal{L}^u_t}\right) + \varepsilon_t,$$

using an OLS regression, where ε_t denotes the regression residual and $g(t)$ is a flexible polynomial of time.[19] Finally, with the estimated value for η at hand, we use the firms' first-order conditions (Equation (8)) to pin down X_t and d_t for $t = 1940, 1950, ..., 2020$.

Numerical methodology. Our structural model assumes that the economic environment is stationary before $t = 1910$ and after $t = 2050$. For a given vector of model parameters Θ, we solve the model backward along the transition path, then forward to recover aggregate quantities and prices, and iterate until convergence. In practice, we use an iterative trial-and-error procedure to minimize the distance between model-generated moments $m(\Theta)$ and their empirical counterparts ψ.

[19] In practice, $g(t)$ is a cubic polynomial of time. Acemoglu & Autor (2011) consider a linear trend as their data begin in the mid-1960s. The evolution of the college premium in Figure 2, panel (a), suggests that a linear trend is indeed a good approximation after the 1960s. When adding data from the early 1940s, it seems sensible to allow for a non-linear trend. This is confirmed in the OLS estimation: the non-linear trend terms are significant at the 1% level. Goldin & Katz (2007) analyze data from the mid-1910s. They use a linear trend but allow the slope of the trend to change between sub-periods.

4.2 Estimation results

4.2.1 Model fit

Empirical targets. Appendix D reports all statistics regarding the model fit. We show that the model provides a good fit for wages across all cohorts and ages for both skilled and unskilled workers. The model thus captures both cross-sectional and cohort-based stylized facts from Section 2.

The model also replicates the rise in skilled labor's share across cohorts as observed in the data. Notably, it captures the sharp increase in college attainment before 1990, followed by a marked deceleration thereafter. This shift in educational attainment pace, captured by the model's educational choice equation (1), is illustrated in Figure 1. Furthermore, the model reproduces the slowdown in college-related earnings gains for post-1990 cohorts. After the 1990 cohort, gains from college education remain high but stop increasing. Meanwhile, the data show a continued rise in the college premium (Figure 2, panel (a)). The model successfully captures both features – stagnant gains from college education alongside a rising college premium – by attributing the latter primarily to declining average wages among non-college workers, as shown further below in Figure 6.

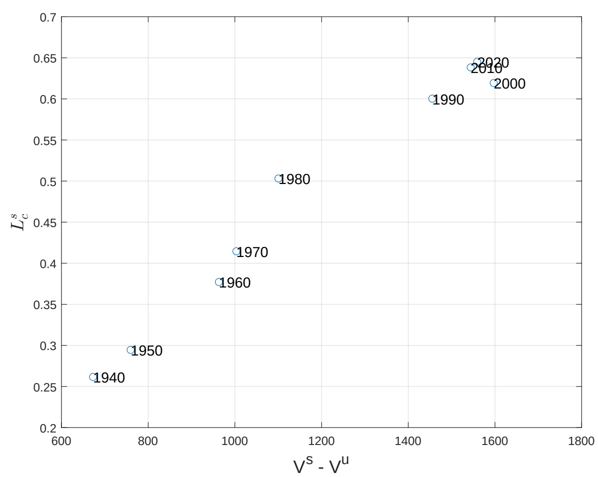
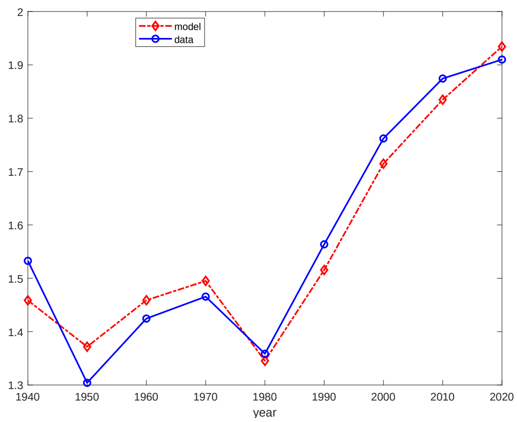


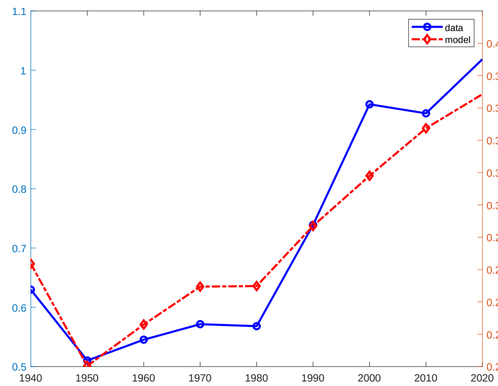
Figure 1: Supply of college workers (L_c^s) and college attendance expected gains ($V_c^s - V_c^u$)

NOTE: Share of college-educated individuals among young workers for each cohort entering the labor market between 1940 and 2020, L_c^s, plotted against the expected gains from college attendance faced by young workers, $V_c^s - V_c^u$.

Wage inequality. The model successfully replicates key features in between-group wage inequality changes, including the double dip in the college premium in 1950 and 1970, as well as the steep increase observed after 1980 (Panel (a) of Figure 2). To assess overall wage inequality, Panel (b) of Figure 2 reports the coefficient of variation of wages. The data (left axis) show an average value of 0.71, compared to 0.29 in the model (right axis), implying that the model accounts for about 40% of observed inequality. While too stylized to match inequality levels precisely, the model reproduces key trends: the V-shaped pattern from the 1940s to 1960s, stagnation in the 1970s, and the rise in recent decades.



(a) College premium



(b) Changes in overall wage inequality

Figure 2: College premium and overall wage inequality: Model vs. data

NOTE: IPUMS U.S. Census 1940-2019 and authors' own calculations. Real weekly wage (in 2010 U.S. dollars) of full-time, full-year working men. Data: solid lines. Model: dashed lines.

4.2.2 Estimated parameters

Time- (and cohort-)invariant parameters. We report in Table 3 the estimated values for parameters that are common across cohorts. The depreciation rate of human capital is estimated at 10% over a 10-year horizon, which is approximately 1% per year. In Huggett et al. (2011), the depreciation rate of human capital is around 2% per year, but the authors also point out that this value may be overestimated due to time allocated to work and learning being the same at each age.

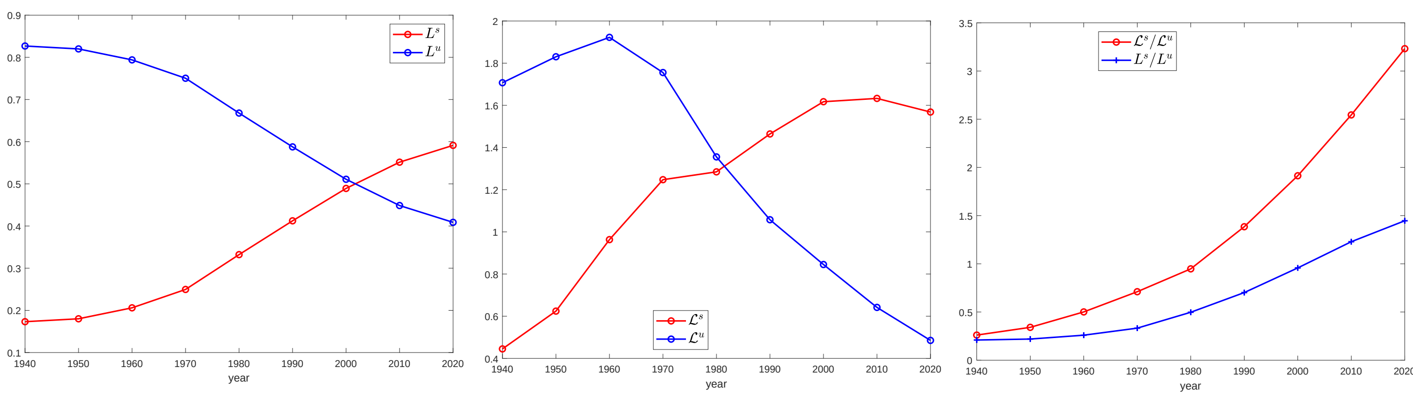
The curvature of the production function of human capital is 0.75 for both skilled and unskilled workers. Our structural estimation yielding the same value for both worker types aligns with the modeling choices in Guvenen & Kuruscu (2010) and is consistent with the confidence intervals reported in Heckman et al. (1998). Regarding the levels, Guvenen & Kuruscu (2010) calibrate ζ to 0.8, while Heckman et al. (1998) consider values between 0.83 and 0.94. Our estimates are slightly lower than these values. This difference may be explained by the sample time periods used for estimation. For instance, Heckman et al. (1998) use data from the early 1960s onward, whereas we consider data starting in the early 1940s.

Table 3: Common parameter values

Parameters		Value
δ	Human capital depreciation rate	10%
ζ^s	Curvature of human capital prod. function $(eh)^{\zeta^s}$, skilled	0.75
ζ^u	Curvature of human capital prod. function $(eh)^{\zeta^u}$, unskilled	0.75
η	Elasticity of substitution between skilled and unskilled $\frac{1}{1-\eta}$	2.06

NOTE: Values of parameters shared across cohorts from the estimated model.

Finally, the elasticity of substitution between skilled and unskilled workers in the CES production function is estimated at $\frac{1}{1-\eta} = 2.06$, well within the range of 1 to 2.5 commonly found in the literature (Katz & Autor (1999)). This value is notably lower than the estimate of 5.3 reported by Bowlus et al. (2023). The magnitude of this elasticity is crucial for decomposing the factors driving the college premium. A higher elasticity of substitution implies a smaller impact of shifts in relative labor supplies on the college premium (see equation (13)). Bowlus et al. (2023) find that, with their larger elasticity estimate, only a modest increase in SBTC is needed to explain the observed increase in relative skill prices.



(a) Labor supply L_t^z **(b)** Efficient Labor $\mathcal{L}_t^z$ **(c)** Relative Labor supply $\frac{L_t^s}{L_t^u}$ and $\frac{\mathcal{L}_t^s}{\mathcal{L}_t^u}$

Figure 3: Labor supply and efficient labor units

NOTE: Population shares and efficient labor units of skilled vs. unskilled workers, overall and expressed in relative terms.

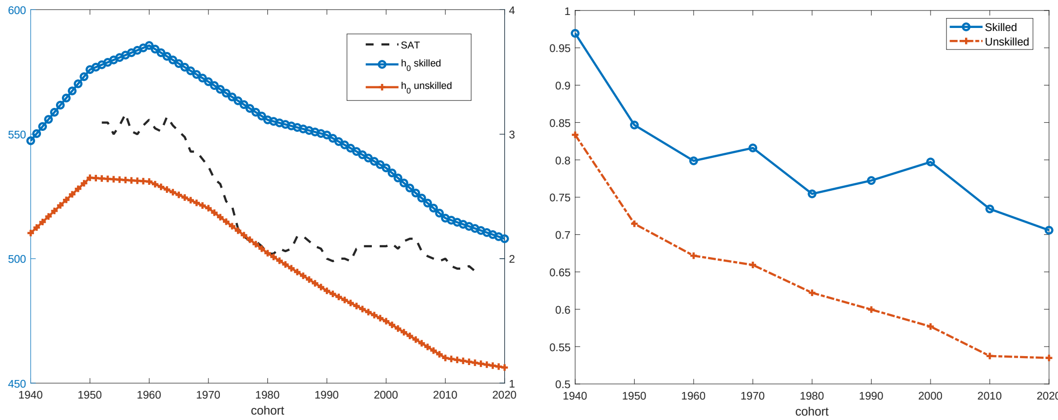
We conjecture that the smaller elasticity in our estimation reflects substitution between heterogeneous worker types rather than homogeneous workers as assumed in the literature. Figure 3, reporting the aggregate supply of skilled and unskilled workers (panel (a)) together with efficient labor by skill level (panel (b)), illustrates this point. The dynamics in panel (a) are quite different from those in panel (b). For example, in 1980, the number of college workers (L_c^s) is half that of non-college workers (L_c^u), but they are equal in terms of efficient labor units (i.e., $\mathcal{L}_c^s = \mathcal{L}_c^u$ in 1980). By 2000, when the number of college and non-college workers intersect, efficient labor units from college workers are twice those from non-college workers. The fact that the increase in efficient skilled labor ($\mathcal{L}_t^s$) exceeds the rise in the number of skilled workers (L_t^s) helps explain the moderate growth in the relative price of human capital (R_t^s/R_t^u, Figure 6, panel (a)), despite the strong estimated SBTC shift benefiting skilled workers (d_t, Figure 5, panel (b)).[20] Panel (c) in Figure 3 provides a measure of the larger increase in relative employment when measured in efficiency units than when measured in headcounts.

Cohort-specific parameters. Figure 4, panel (a) reports the estimated human capital endowments upon labor market entry, $h_{0,c}^z$. After a rise in initial human capital from the early 1940s to the 1960 cohort, Figure 4 suggests that $h_{0,c}$ declines. We interpret the fall in $h_{0,c}$ as a decline in the abilities of young workers for post-1960s cohorts. This finding dovetails with declining SAT scores observed in the data (also reported in panel (a) of Figure 4). Hayes et al. (1996) link this dynamics to the simplification of school textbooks since the 1970s, arguing that reduced textual complexity contributed to deteriorating verbal skills among high school students. These patterns are also consistent with evidence of falling academic selectivity (Hoxby (2009)) and reduced study effort among college students since the early 1960s (Babcock & Marks (2011)), suggesting a broad deterioration in young workers' human capital.

Figure 4, panel (b), reports the estimated, cohort-specific ability-to-learn parameter α_c^z. First, we find higher ability-to-learn for skilled than for unskilled workers, a standard result in the literature (see Belzil et al. (2017)). Second, our estimation indicates declining α_c^z values for more recent cohorts, albeit at a slower rate for skilled workers. We can only speculate about why this might be the case, but in our view a promising explanation lies in the many labor market changes that have eroded the returns to human capital investments. While Engbom (2022) shows that wages grow more over the life-cycle in more fluid labor markets (as job-to-job mobility allows workers to find jobs where their skills are most valued), a large literature documents declining labor market fluidity in the U.S. (see Molly et al. (2016) and others). Likewise, the so-called falling job ladder (Baksy et al. (2024)) leads to reduced earnings gains from human capital investments.

Aggregate shocks: X_t and d_t. Figure 5 reports the estimated time paths of X_t and d_t. As shown, X_t rises initially during the post-WWII economic boom – a period of rapid

[20] Property 1 in Section 3.4 provides intuition for this result. When workers make OJT decisions, they take the aggregate rental price of labor R_t^z and the productivity benefits they receive from other workers' OJT efforts as given. Consequently, they invest more in human capital than in a scenario where they could internalize these general equilibrium spillovers.

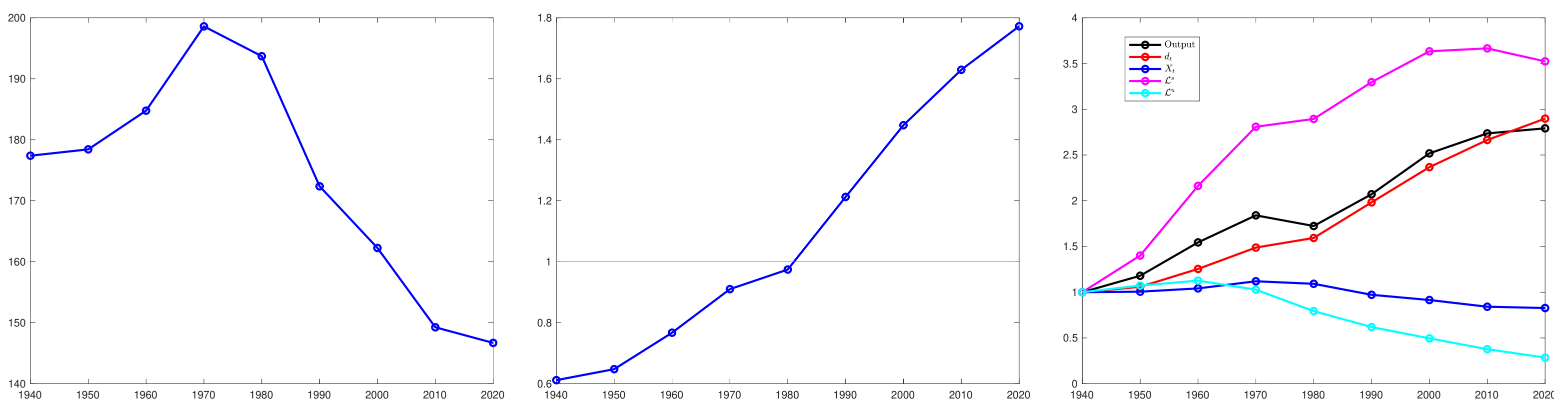


(a) Initial human capital endowments $h^z_{0,c}$ **(b)** Ability to learn α^z_c

Figure 4: Cohort-specific parameter values $\{\alpha^z_c, h^z_{0,c}\}^{2020}_{c=1910}$, $z \in \{s, u\}$

NOTE: Values of cohort-specific parameters for the estimated model. Panel (a): the dashed line shows SAT scores (plotted against the left axis) from the National Center of Education Statistics.

growth in output and wages. After 1970, however, X_t begins to decline. While this may appear surprising, the time path of X_t is fully consistent with the estimation strategy of targeting wage dynamics rather than output directly. Specifically, the downward trajectory of X_t likely captures the structural decline in the labor share, a well-documented empirical phenomenon beginning in the 1970s (Karabarbounis & Neiman (2014)).[21]



(a) Skill-neutral technological change X_t **(b)** Skill-biased technological change d_t **(c)** Decomposition of output growth

Figure 5: Aggregate shocks and output growth decomposition

NOTE: Values of the aggregate technological shocks from the estimated model and their contribution to output growth.

[21]Several explanations of the falling labor share have been proposed, including the weakening of workers' bargaining power due to declining unionization and labor market deregulation (Farber et al., 2021, Stansbury & Summers, 2020), and the long-run erosion of the real minimum wage (Lee (1999b), Autor et al. (2016) and Footnote 15 above).

In panel (b) of Figure 5, the growth of d_t accelerates after 1980, continues to rise through the 1990s, and then slightly slows down in the 2000s. This pattern aligns with the historical narrative of computer adoption in the 1980s, ICT diffusion in the 1990s, and a subsequent slowdown in technological progress following the "dot-com bust". It is noteworthy that our model generates this realistic profile for the technological progress, as Acemoglu & Autor (2011) observe that the canonical model, using equation (13), predicts a *deceleration* of SBTC (relative demand for high-skilled workers) in the 1990s. However, this prediction "*does not accord with common intuitions regarding the nature or pace of technological change occurring in this era*", as Acemoglu & Autor (2011) argue.[22]

Panel (c) of Figure 5 provides a decomposition of output growth since the postwar period: output, corresponding to the economy's wage bill, has increased by a factor of 2.5, driven primarily by the expansion of efficient skilled employment ($\mathcal{L}_t^s$), which has risen more than 3.5-fold, and by SBTC (d_t), which has more than doubled. In contrast, efficient unskilled employment ($\mathcal{L}_t^u$) has declined, as has skill-neutral technological progress (X_t).

4.3 Key mechanisms

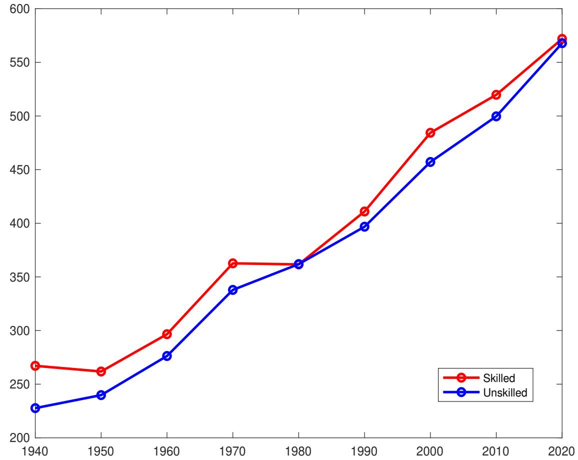
Finally, we highlight key mechanisms that emerge from the estimated model to explain the earnings gap between unskilled and skilled workers, the growth of lifetime wages, and their dynamics across cohorts.

Stable R_t^s/R_t^u vs. rising Y_t^s/Y_t^u. Figure 6 reveals a striking finding from the estimated model. Panel (a) shows that the *relative price* of skilled labor (R^s) to unskilled labor (R^u) remains remarkably stable from 1940 to 2020. The two price series increase in levels due to common aggregate trends (X_t) and complementarity in the production function, but the key point is that their ratio is essentially flat. This implies that prices alone cannot explain the widening wage gap between skill groups.

In contrast, Panel (b) of Figure 6 displays the evolution of average wages, Y_t^z, $z \in \{s, u\}$, which depend on aggregate labor efficiency units of all age groups ℓ_t^z priced at R_t^z. There is substantial divergence: the wages of skilled workers rise steadily over time, while those of unskilled workers decline after the 1970s. Given stable relative prices, this divergence necessarily reflects changes in the relative supply of efficient labor units.

Sources of the dynamics of $\mathcal{L}_t^s/\mathcal{L}_t^u$. The previous paragraphs highlight the importance of a quantity effect, namely changes in $\mathcal{L}_t^s/\mathcal{L}_t^u$. To unpack the sources of these dynamics,

[22] Heckman et al. (1998) and Guvenen & Kuruscu (2010) make assumptions about the pace of SBTC, contrary to our strategy of estimating by fitting the model to aggregate wage data.



(a) Price of human capital $\{R_t^s; R_t^u\}$ **(b)** Average wages $\{Y_t^s; Y_t^u\}$

Figure 6: Price of human capital and average wages

NOTE: Price of human capital and average wages from the estimated model.

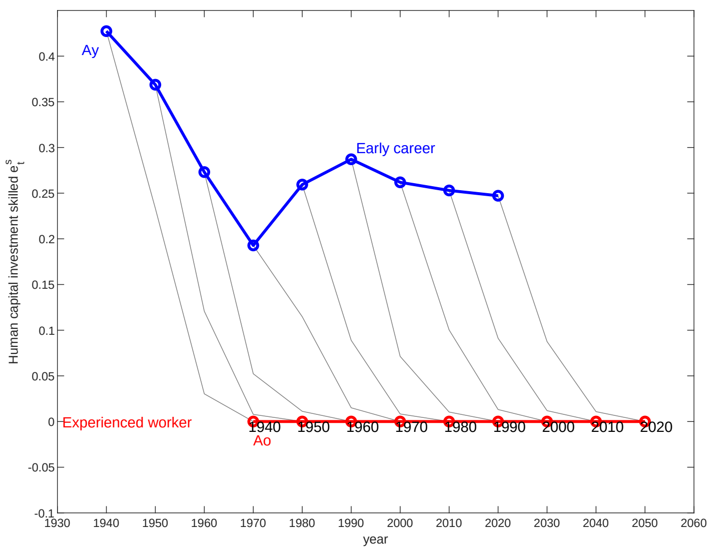
Figure 7 reports the life-cycle profiles of OJT and accumulated human capital across cohorts and skill groups. First, panels (a) and (c) show time allocated to OJT. Workers from early cohorts, such as those entering in 1940, devote up to 40% of their time to training at the beginning of their careers.[23] Over time, this effort declines, particularly among unskilled workers. The 1970 cohort marks a turning point: skilled workers maintain sustained OJT effort, devoting 25% of their time endowment to OJT, while unskilled workers reduce their efforts sharply to 15% of their time. This behavioral divergence sets the stage for growing inequality in human capital accumulation.

Panels (b) and (d) of Figure 7 illustrate how these differences in OJT translate into accumulated human capital. Skilled workers not only start with higher initial human capital (e.g., $h^s_{0,1940} \approx 2.95$ versus $h^u_{0,1940} \approx 2.21$; Figure 4), but also continue to accumulate it throughout their careers. For more recent cohorts, skilled old workers' human capital stock is still larger than what they had upon labor market entry, despite lower initial endowments. In contrast, unskilled workers experience a decline both in initial human capital and in subsequent accumulation, leading to flatter or even declining wage profiles.[24]

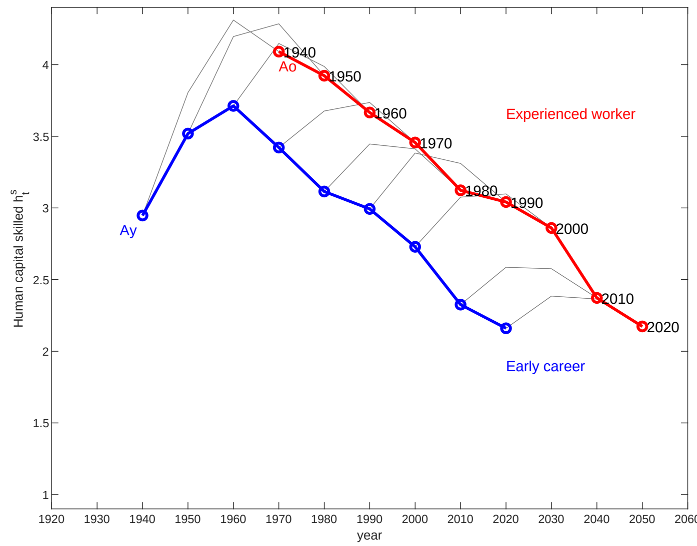
It is also useful to relate Figure 7 to the estimated parameters shown in Figure 4. Skilled workers benefit from higher learning ability ($\alpha^s_c > \alpha^u_c$) and higher human capital endowments

[23] Figure 7 shows that, assuming a 40-hour workweek, our model predicts young skilled workers from the 1940 cohort devote 7.7 hours weekly to on-the-job training, rising to 10.5 hours weekly for later cohorts. These estimates fall within the lower range reported by Barron et al. (1997) for new hires and by Loewenstein & Spletzer (2000) using NLSY data.

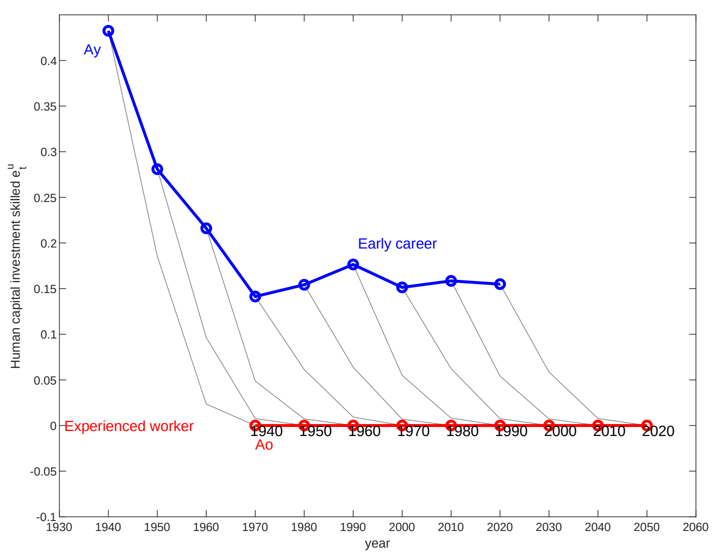
[24] A key aspect of human capital accumulation is what Cunha & Heckman (2007) describe as "dynamic complementarities": a higher stock of human capital tomorrow increases the returns to human capital investments, which in turn boosts human capital today.



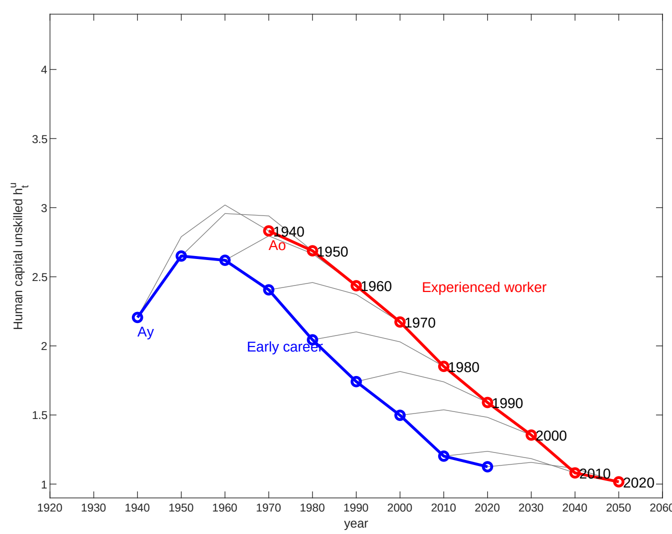
(a) OJT $e_{c,a}$ - Skilled workers



(b) Human capital $h_{c,a}$ - Skilled workers



(c) OJT $e_{c,a}$ - Unskilled workers



(d) Human capital $h_{c,a}$ - Unskilled workers

Figure 7: On-the-job training and human capital by age, cohort and skill level

NOTE: Panels (a) & (c): Optimal on-the-job training (OJT) $e_{a,c}$. "Ay": Young skilled (unskilled) workers in 1940 devote 42% (43%) of their time endowment to OJT. "Ao": In 1970, the 1940-young workers have become older; they set OJT to zero. The graph report decision on OJT for each cohort $c = 1940, 1950, ..., 2020$. Panels (b) & (d): Stock of human capital $h_{a,c}$. "Ay": Young skilled (unskilled) workers' human capital in 1940 is $h_{0-9,1940} = 2.95$ (2.21). "Ay" In 1970, the 1940-young workers have become older, their human capital is $h_{30-39,1940} = 4.10$ (2.83).

($h^s_{0,c} > h^u_{0,c}$). While both features of the human capital production function decline among more recent cohorts, the decline is slower for skilled workers, reinforcing their relative advantage over unskilled workers. Although skilled workers spend more time away from direct production (as they invest more in human capital), the productivity gains from OJT (higher $h^z_{a,c}$) more than compensate for the difference in time investments (lower $1 - e^z_{a,c}$), so that their $\ell^z_{a,c} = (1 - e^z_{a,c})h^z_{a,c}$ remains higher compared to their unskilled counterparts.

5 Counterfactual scenarios

We now use counterfactual experiments to disentangle the roles of aggregate and cohort-specific shocks as well as endogenous adjustment mechanisms in shaping wage profiles and inequality. Since 1970 appears as a turning point in much of the dynamics highlighted in the previous section, we typically run counterfactual calculations by "freezing" parameters or variables at their 1970 values.[25]

5.1 Constant aggregate and cohort-specific shocks

In the first set of counterfactual experiments, we hold constant at their estimated 1970 levels either the aggregate technology shocks X_t and d_t or the cohort-specific human capital production factors $h^z_{0,c}$ and α^z_c. These experiments jointly show that changes in the macro environment, whether technological or sociodemographic, are necessary to reproduce the observed pattern of rising wage inequality since the 1970s.

No SBTC (d_t): Falling lifetime wage growth, but college premium still rises. Holding d_t fixed at its 1970 level, we shut down rising SBTC. Table 4 shows that this leads to a collapse in lifetime wage growth: for the 1990 cohort, wage growth falls to 0.71 for unskilled workers and 0.80 for skilled workers (column (3)). This confirms the importance of SBTC in sustaining upward-sloping life-cycle earnings profiles. However, as shown in Table 5, the college premium in 2020 remains high at 1.97 (versus 1.93 in baseline; column (4)), and even rises slightly in 1970 (1.57 vs. 1.49 in baseline; column (2)). This counterintuitive result arises because unskilled cohorts experience a more pronounced decline in effective labor units when SBTC is suppressed. Indeed, in an environment with strong SBTC and imperfect substitutability between skilled and unskilled labor, unskilled workers benefit indirectly from the rising productivity of skilled workers.

[25] We highlight the most important results in this section and report the full set of model predictions in Appendix E .

No macro trend (X_t): Steeper lifetime wage growth, smaller college premium. Next, suppose that aggregate shocks X_t remain fixed at their 1970 value instead of experiencing the series of negative shocks portrayed in Figure 5. According to our model, lifetime wage growth would have been substantially higher for post-1970 cohorts. For example, wage growth for the 1990 cohort would have reached 2.67 for unskilled and 3.14 for skilled workers, compared to 1.58 and 1.98 in the baseline (Table 4, column (3)). The college premium in 2020 would have dropped to 1.69 (Table 5, column (4)), versus 1.93 in the baseline. This scenario illustrates that X_t acts as a level shifter across all groups but disproportionately benefits low-skilled workers, compressing the college premium. In this sense, the aggregate skill-neutral shifter X_t acts as an equalizing force.

No cohort trend ($h_{0,c}$, α_c): lifetime wage growth rebounds, lower college premium. Finally, in Tables 4 and 5, we consider the effect of freezing human capital endowments and learning ability at their estimated 1970 levels, thereby halting the decline observed among more recent cohorts. As shown, this raises wage growth across the board, especially for skilled workers: 2.19 (Table 4, column (3)), versus 1.98 in the baseline. At the same time, this leads to a lower college premium in 2020, namely 1.59 (Table 5, column (4)) versus 1.93 in the baseline. This scenario underscores that the post-1970 decline in $h_{0,c}$ and α_c, especially among unskilled workers, is a key structural driver of stagnating wage profiles and rising inequality.

5.2 Disabling endogenous responses

In the second set of counterfactual experiments, we examine the consequences of suppressing two endogenous mechanisms: cohort-specific changes in educational attainment reflected in L_c^s and changes in the aggregate skill prices R_t^z for $z \in \{s, u\}$. The stark result emerging from these experiments is that in the absence of such adjustment mechanisms, wage inequality rises massively.

No education expansion (L_c^s): Asymmetric wage profiles and explosive college premium. If the share of college-educated workers had been held constant at its 1970 level, the college premium in 2020 would rise to 3.03 (Table 5, column (4)) versus 1.93 in the baseline. Skilled workers would in addition experience lifetime wage growth by 2.29, while unskilled workers would experience near-stagnation (a lifetime wage growth rate of 1.12; Table 4, column (3)). The intuition is straightforward: the scarcity of skilled labor inflates its price. In this sense, education choices act as a stabilizing force – when more people enroll in college in response to high returns, it prevents the college premium from spiraling upward.

Table 4: Lifetime wage growth

Cohort c	1940	1970	1990
Years t in the labor market	$1940-1970$	$1970-2000$	$1990-2020$
	(1)	(2)	(3)
Unskilled workers			
Baseline	3.35	1.42	1.58
Aggregate and cohort-specific shocks:			
Fixed d_t	3.30	0.73	0.71
Fixed X_t	3.36	2.22	2.67
Fixed $\{h_{0,c}^z, \alpha_c^z\}$, $z \in \{s,u\}$	1.61	1.34	1.48
Aggregate and cohort-specific responses:			
Fixed L_c^s	3.33	1.16	1.12
Fixed R_t^z, $z \in \{s,u\}$	1.64	0.70	0.73
Skilled workers			
Baseline	3.29	1.67	1.98
Aggregate and cohort-specific shocks:			
Fixed d_t	3.36	0.72	0.80
Fixed X_t	3.27	2.48	3.14
Fixed $\{h_{0,c}^z, \alpha_c^z\}$, $z \in \{s,u\}$	1.83	1.77	2.19
Aggregate and cohort-specific responses:			
Fixed L_c^s	3.32	1.93	2.29
Fixed R_t^z, $z \in \{s,u\}$	11.75	1.58	1.52

NOTE: : Lifetime wage growth as measured by $y_{30-39,c}^z / y_{0-9,c}^z$. 'Baseline' presents model outcomes with the full dynamics coming from aggregate and cohort-specific shocks and responses. The rest of the table presents model outcomes where either aggregate or cohort-specific shocks or responses are held constant to their estimated value(s) in 1970.

Table 5: The college premium

Year t	1940	1970	1990	2020
	(1)	(2)	(3)	(4)
Baseline	1.46	1.49	1.51	1.93
Aggregate and cohort-specific shocks:				
Fixed d_t	1.45	1.57	1.55	1.97
Fixed X_t	1.46	1.46	1.40	1.69
Fixed $\{h_{0,c}^z, \alpha_c^z\}$, $z \in \{s,u\}$	1.51	1.55	1.52	1.59
Aggregate and cohort-specific responses:				
Fixed L_c^s	1.45	1.48	1.82	3.03
Fixed R_t^z, $z \in \{s,u\}$	0.86	1.20	1.81	3.53

NOTE: The college premium as measured by Y_t^s / Y_t^u. 'Baseline' presents model outcomes with the full dynamics coming from aggregate and cohort-specific shocks and responses. The rest of the table presents model outcomes where either aggregate or cohort-specific shocks or responses are held constant to their estimated value(s) in 1970.

This dynamic feedback is typically absent from partial equilibrium analyses. In addition, as skilled workers benefit from a booming price of their skill, their expected wage growth over careers becomes much larger than in baseline.

Exogenous skill prices (R_t^z, $\eta = 1$): Extreme inequality and output collapse. Finally, we assess the importance of endogenous adjustments in skill prices. To do so, we impose a linear production function ($\eta = 1$), as in Guvenen & Kuruscu (2010), which implies that the rental price of effective labor units is determined only by the aggregate shifters and no longer responds to endogenous variation in labor supply.

As Table 5 shows, holding R_t^z constant breaks the price feedback loop, making the college premium reach 3.53 in 2020 (Table 5, column (4)) versus 1.93 in the baseline). Moreover, Table 4 indicates that skilled workers from the 1990 cohort still see their earnings increase over the life cycle (1.52 versus 1.98 in the baseline; Table 4, column (3)), while unskilled workers experience near-zero wage growth (0.73). Additionally, in appendix Figure 13, we report that aggregate output in this experiment remains essentially stagnant over the period analyzed (in other words, it drops relative to output in the baseline experiment). This highlights the fundamental equilibrating mechanism coming from skill prices. Without it, wage inequality explodes and aggregate performance is severely compromised.

5.3 Sensitivity analysis

The results of our counterfactual scenarios are based on a structural model and thus depend on the quality and fit of our model estimation. In Appendix F, we conduct a detailed analysis of local identification of our model's parameters. We find that the Jacobian matrix has full rank, indicating that no parameter is redundant or a linear combination of others.

Our model assumes that agents have perfect foresight over the future paths of aggregate shocks and prices. In Appendix G, we show that our findings remain valid even under the extreme assumption of myopic behavior. The intuition is straightforward: what matters for human capital decisions is the expected change in its price (see Figure 6); this price steadily increases for both skill levels, so that even myopic workers are incentivized to invest more in OJT and to pursue higher education in an economy where the price of human capital is expected to rise. Some quantitative differences relative to the baseline model emerge, but the main results are preserved under myopic expectations.

Finally, the baseline results are obtained using data on full-time, full-year working men. We report in Appendix H stylized facts, estimated parameters, and counterfactual experiments when full-time, full-year working women are included in the sample. We show that our main results continue to hold.

6 Conclusion

Our paper sheds new light on the factors that have contributed to the evolution of U.S. wage inequality in the post-WWII era. First, aggregate technological shocks affecting all job and worker types as well as skill-biased technological change. Second, cohort-specific changes in the parameters governing human capital accumulation, including human capital endowments upon labor market entry and the ability to learn over the working life. Third, endogenous adjustments in educational attainment and equilibrium responses of skill prices. Our framework contributes by quantifying the contribution of these forces within a unified general equilibrium model matching cross-sectional and cohort wage data.

Based on counterfactual experiments, we find that changes in the macro environment, whether technological or sociodemographic, are necessary to reproduce the observed pattern of rising wage inequality since the 1970s. The deterioration of cohort-specific human capital production parameters plays a critical role in the flattening of lifetime wage profiles, especially for non-college workers. Endogenous mechanisms – education choices and price feedbacks – act as stabilizing forces. Without them, the increase in the college premium and the rebound of lifetime wage profiles become extreme.

While we do not simulate specific policy interventions, the logic of the model itself – how education and skill accumulation decisions interact with general equilibrium prices and the dynamics of overlapping cohorts – naturally provides some insights. First, the model indicates that tuition subsidies or broad-based expansion of college access may have indirect effects on older generations. Since wages are determined in general equilibrium and reflect the aggregate supply of skilled labor, any increase in the number or quality of young college graduates puts downward pressure on the skill premium earned by older cohorts who are still active in the labor market. These intergenerational spillovers imply that the impact of such policies should not be assessed solely based on their direct beneficiaries – young workers. Second, the model highlights a forward-looking disincentive effect that can arise in periods of rapid educational expansion. When individuals expect a continued rise in the supply of skilled workers, they anticipate lower future returns to skill and rationally scale back their effort in post-education human capital accumulation, particularly OJT. This mechanism suggests that increasing the quantity of college graduates may not translate into proportional gains in the effective skill level of the workforce. While we do not quantify policy trade-offs explicitly, this logic suggests that expanding access without complementary policies to sustain quality may yield limited gains in productivity or equity.

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Online appendix

A Data appendix

We use decennial IPUMS US Census data from 1940 through 2020.[26] Following standard practice in the literature (Katz & Murphy (1992), Jeong et al. (2015), among others), we focus our main analysis on full-time, full-year male workers (with results for women reported in Appendix H). Specifically, we include only employed men working for wages who report at least 35 weekly hours and over 39 weeks of work during the year.[27] We exclude workers in farming and fishery occupations as well as members of the armed forces. Finally, we restrict our sample to individuals aged 16 to 59.

Non-college workers include high school graduates and high school dropouts, while college workers include individuals with some college, BA, MA, and PhD degrees.[28]

Throughout the paper, we refer to cohorts by the year they entered the labor market. We use "age" to mean "age in the labor market", which corresponds to work experience measured as years since completing education. We infer the age at which education ended from completed education levels. This proxy is likely accurate for male workers, who experience fewer career interruptions than female workers. Given that Census data is collected decennially, we categorize workers into four experience groups: 0-9 years of work experience ("young" workers), 10-19 years, 20-29 years, and 30-39 years ("old" workers).

Our main earnings variable is the real weekly wage, calculated as annual wage divided by the number of weeks worked. We use the CPI to convert all wages into 2010 dollars.

[26] We refer to our final data point as "2020" throughout the paper, though we use 2019 Census data as our endpoint to avoid pandemic-related outliers from 2020.

[27] We follow Kong et al. (2018) to determine weekly hours worked.

[28] Note that we define skilled workers as those with some college or more, and unskilled workers as high school graduates and dropouts. Other papers, such as Acemoglu & Autor (2011), compare only college graduates versus high school graduates, so their college premium measures the relative wage between these two specific groups. Our broader classification corresponds to our model's requirement to partition workers into two groups, while studies like Acemoglu & Autor (2011) aim to contrast groups with distinctly different educational attainment levels.

B Analytical solutions for the Ben-Porath model

This section presents analytical solutions for the Ben-Porath model. Most importantly, we show that all structural parameters can be identified without imposing any normalization.

Proposition 1. *The value functions $V^z_{c,a}$ are linear functions with respect to $h^z_{c,a}$:*

$$V^z_{c,a}(h^z_{c,a}) = A^z_{c,a}h^z_{c,a} + B^z_{c,a}(\alpha^z_c) \quad \forall a, c, z \tag{15}$$

Proof. Guess that (15) holds at age $a = 30$ (the terminal age). Then $A^z_{c,30} = R^z_{c+30}$ and $B^z_{c,A}(\alpha^z_c) = 0$ since $e^z_{30,c} = 0$ (see Equation (3)). Under this assumption, the FOC for $e^z_{c,a}$ is

$$R^z_{c+a} = \beta A^z_{c,a+1}\alpha^z_c\zeta^z_c(e^z_{c,a}h^z_{c,a})^{\zeta^z_c-1} \quad \Rightarrow \quad \begin{cases} e^z_{c,a}h^z_{c,a} &= \left(\frac{\beta\zeta^z_c\alpha^z_c A^z_{c,a+1}}{R^z_{c+a}}\right)^{\frac{1}{1-\zeta^z_c}} \\ R^z_{c+a}e^z_{c,a}h^z_{c,a} &= \beta A^z_{c,a+1}\alpha^z_c\zeta^z_c(e^z_{c,a}h^z_{c,a})^{\zeta^z_c} \end{cases} \tag{16}$$

Using Equations (5), (15) and (16), the value function at age a is then

$$\begin{aligned} V^z_{c,a}(h^z_{c,a}) &= R^z_{c+a}\left(1 - e^z_{c,a}\right)h^z_{a,c} + \beta V^z_{c,a+1}(h^z_{c,a+1}) \\ &= \underbrace{\left[R^z_{c+a} + \beta(1-\delta^z)A^z_{c,a+1}\right]}_{A^z_{c,a}} h^z_{a,c} + \underbrace{\left(\frac{1}{\zeta^z_c} - 1\right)R^z_{c+a}\left(\frac{\beta\zeta^z_c\alpha^z_c A^z_{c,a+1}}{R^z_{c+a}}\right)^{\frac{1}{1-\zeta^z_c}} + \beta B^z_{c,a+1}(\alpha^z_c)}_{B^z_{c,a}(\alpha^z_c)} \end{aligned}$$

which satisfies Equation (15) and yields expressions for $A^z_{c,a}$ and $B^z_{c,a}(\alpha^z_c)$. □

Proposition 2. *The parameter sets $\{h^z_{c,0}, \alpha^z_c, R^z_{c+a}\}^{30}_{a=0}$ and $\{\frac{h^z_{c,0}}{\lambda}, \frac{\alpha^z_c}{\lambda^{1-\zeta^z}}, \lambda R^z_{c+a}\}^{30}_{a=0}$ generate different wage sequences $\{y^z_{c,a}\}^{30}_{a=0}$.*

Proof. Note that $A^z_{c,a} = R^z_{c+a} + \beta(1-\delta^z)A^z_{c,a+1} \Rightarrow A^z_{c,a} = \sum^{30}_{i=a}[\beta(1-\delta^z)]^{i-a}R^z_{c+i}$. Therefore, multiplying R^z_{c+i} by λ also multiplies $A^z_{c,a}$ by λ, while leaving $B^z_{c,a}(\alpha^z_c)$ and $e^z_{c,a}h^z_{c,a}$ unchanged. Using Equations (5) and (16), we obtain:

$$\begin{aligned} h^z_{c,a} &= (1-\delta^z)^a h^z_{c,0} + \sum^{a-1}_{i=0}(1-\delta^z)^{a-1-i}\alpha^z_c(e^z_{c,a}h^z_{c,a})^{\zeta^z_c} \\ &= (1-\delta^z)^a h^z_{c,0} + (\alpha^z_c)^{\frac{1}{1-\zeta^z}} \underbrace{\sum^{a-1}_{i=0}(1-\delta^z)^{a-1-i}\left(\beta\zeta^z_c\frac{A^z_{c,a+1}}{R^z_{c+a}}\right)^{\frac{\zeta^z}{1-\zeta^z_c}}}_{C^z_{c,a}} \\ \Rightarrow \quad y^z_{c,a} &\equiv h^z_{c,a}R^z_{c+a}(1-e^z_{c,a}) = (1-\delta^z)^a h^z_{c,0}R^z_{c+a}(1-e^z_{c,a}) + (\alpha^z_c)^{\frac{1}{1-\zeta^z_c}}C^z_{c,a}R^z_{c+a}(1-e^z_{c,a}). \end{aligned}$$

Compare the wage sequences generated by the parameter set $\{h^z_{c,0}, \alpha^z_c, R^z_{c+a}\}^A_{a=0}$ vs. parameter set $\{\frac{h^z_{c,0}}{\lambda}, \frac{\alpha^z_c}{\lambda^{1-\zeta^z}}, \lambda R^z_{c+a}\}_{a=0}^A$, respectively given by:

$$
\begin{aligned}
y^z_{c,a} &= (1-\delta^z)^a h^z_{c,0} R^z_{c+a}(1-e^z_{c,a}) + (\alpha^z_c)^{\frac{1}{1-\zeta^z_c}} C^z_{c,a} R^z_{c+a}(1-e^z_{c,a}), \\
\text{vs.} \quad y^z_{c,a} &= (1-\delta^z)^a \frac{h^z_{c,0}}{\lambda}(\lambda R^z_{c+a})(1-e^z_{c,a}) + \left(\frac{\alpha^z_c}{\lambda^{1-\zeta^z_c}}\right)^{\frac{1}{1-\zeta^z_c}} C^z_{c,a}(\lambda R^z_{c+a})(1-e^z_{c,a}).
\end{aligned}
$$

The wage sequences are identical if and only if $e^z_{c,a}$ is identical under both parameter sets. We show that this cannot hold. Indeed, compare the $h^z_{c,a}$ obtained under each set of parameters:

$$
\begin{aligned}
h^z_{c,a} &= (1-\delta^z)^a h^z_{c,0} + (\alpha^z_c)^{\frac{1}{1-\zeta^z_c}} C^z_{c,a}, \\
\text{vs.} \quad h^z_{c,a} &= (1-\delta^z)^a \frac{h^z_{c,0}}{\lambda} + \left(\frac{\alpha^z_c}{\lambda^{1-\zeta^z_c}}\right)^{\frac{1}{1-\zeta^z_c}} C^z_{c,a} = \frac{1}{\lambda}\left[(1-\delta^z)^a h^z_{c,0} + (\alpha^z_c)^{\frac{1}{1-\zeta^z_c}} C^z_{c,a}\right].
\end{aligned}
$$

Given that $C^z_{c,a}$ is identical under both parameter sets, this shows that

$$
h^z_{c,a}\big|_{\{\frac{h^z_{c,0}}{\lambda}, \frac{\alpha^z_c}{\lambda^{1-\zeta^z}}, \lambda R^z_{c+a}\}_{a=0}^A} = \frac{1}{\lambda} h^z_{c,a}\big|_{\{h^z_{c,0}, \alpha^z_c, R^z_{c+a}\}_{a=0}^A}.
$$

However, $e^z_{c,a} h^z_{c,a}$ is identical under both sets of parameters. This in turn implies that

$$
e^z_{c,a}\big|_{\{\frac{h^z_{c,0}}{\lambda}, \frac{\alpha^z_c}{\lambda^{1-\zeta^z}}, \lambda R^z_{c+a}\}_{a=0}^A} = \lambda e^z_{c,a}\big|_{\{h^z_{c,0}, \alpha^z_c, R^z_{c+a}\}_{a=0}^A},
$$

showing that the two parameter sets lead to different $e^z_{c,a}$. □

Proposition 2 demonstrates that the solution of the Ben-Porath model allows to identify all structural parameters without imposing any normalization.

C Estimation restrictions

Out-of-sample data estimation. The six wage moments $\{y_{1910,1910+a}\}_{a=0}^{20}$, $\{y_{1920,1920+a}\}_{a=0}^{10}$ and $y_{1930,1930+10}$ before 1940 are missing from the data. We estimate them under the assumption that the wage profile is stable before 1940 and given by $y_{c,c+a} = \widehat{\mu}_{c,0} + \widehat{\mu}_1 \times a + \widehat{\mu}_2 \times a^2$, where the estimated values $\widehat{\mu}_1$ and $\widehat{\mu}_2$ are obtained from the average wage profiles of the 1940, 1950, and 1960 cohorts. By observing $y_{1910,1910+30}$, $y_{1920,1920+20}$, $y_{1930,1930+10}$ in the 1940 cross-sectional data, we then recover $\{\widehat{\mu}_{c,0}\}_{c=1910}^{1930}$ as follows:

$$
\begin{aligned}
y_{1930,1930} &= \widehat{\mu}_{1930,0} \quad \text{where} \quad y_{1930,1930+10} = \widehat{\mu}_{1930,0} + \widehat{\mu}_1 \times 10 + \widehat{\mu}_2 \times 10^2,\\
y_{1920,1920} &= \widehat{\mu}_{1920,0} \quad \text{where} \quad y_{1920,1920+20} = \widehat{\mu}_{1920,0} + \widehat{\mu}_1 \times 20 + \widehat{\mu}_2 \times 20^2,\\
y_{1910,1910} &= \widehat{\mu}_{1910,0} \quad \text{where} \quad y_{1910,1910+30} = \widehat{\mu}_{1910,0} + \widehat{\mu}_1 \times 30 + \widehat{\mu}_2 \times 30^2,
\end{aligned}
$$

which in turn yields the estimated values of $\{\{y_{c,c+a}\}_{a=0}^{30}\}_{c=1910}^{1930}$.

The same logic applies to $y_{2000,2000+10}$, $\{y_{2010,2010+a}\}_{a=0}^{10}$, and $\{y_{2020,2020+a}\}_{a=10}^{30}$. The 2020 cross-sectional data provides us with the observed values of $y_{2020,2020}$, $y_{2010,2010+10}$, and $y_{2000,2000+20}$, which we use together with:

$$
\begin{aligned}
y_{2020,2020} &= \widehat{\mu}_{2020,0} \quad \text{where} \quad y_{2020,2020} = \widehat{\mu}_{2020,0},\\
y_{2010,2010} &= \widehat{\mu}_{2010,0} \quad \text{where} \quad y_{2010,2010+10} = \widehat{\mu}_{2010,0} + \widehat{\mu}_1 \times 10 + \widehat{\mu}_2 \times 10^2,\\
y_{2000,2000} &= \widehat{\mu}_{2000,0} \quad \text{where} \quad y_{2000,2000+20} = \widehat{\mu}_{2000,0} + \widehat{\mu}_1 \times 20 + \widehat{\mu}_2 \times 20^2,
\end{aligned}
$$

where the estimated $\widehat{\mu}_1$ and $\widehat{\mu}_2$ are obtained from the average wage profiles of the 1970, 1980, and 1990 cohorts. This yields estimated values of $\{\{y_{c,c+a}\}_{a=0}^{30}\}_{c=2000}^{2020}$.

Stationarity assumptions. With these out-of-sample estimated data at hand, the model can be estimated for the cohorts entering the labor market between 1910 and 2020 under the following stationarity assumptions:

- before (and including) the 1910 decade the economy is at steady state, i.e., $y_{\mathcal{C},\mathcal{C}+a} = y_{\mathcal{C}',\mathcal{C}'+a}$ for all $\mathcal{C} \in (-\infty, 1900]$ and $\mathcal{C}' = 1910$, with these steady-state restrictions propagating as shown in Table 6;

- after 2020, the steady-state restrictions propagate as shown in Table 7.

These stationarity, or steady-state, assumptions make it possible to compute the general equilibrium of the model before 1930 and after 2020 – periods during which individuals from the earlier cohorts (prior to and including 1900) and future cohorts (after 2030) are active in the labor market.

Table 6: Propagation of steady-state restrictions — Before 1910

30	$y_{1910,1910+30}$	$y_{1910,1910+30}$	$y_{1910,1910+30}$	$y_{1910,1910+30}$	$y_{1910,1910+30}$
20	$y_{1910,1910+20}$	$y_{1910,1910+20}$	$y_{1910,1910+20}$	$y_{1910,1910+20}$	$y_{1920,1920+20}$
10	$y_{1910,1910+10}$	$y_{1910,1910+10}$	$y_{1910,1910+10}$	$y_{1920,1920+10}$	$y_{1920,1930+10}$
0	$y_{1910,1910}$	$y_{1910,1910}$	$y_{1920,1920}$	$y_{1930,1930}$	$y_{1940,1940}$
$\mathcal{C}$	$(-\infty, 1900]$	1910	1920	1930	1940

NOTE: The gray-shaded values correspond to the restrictions implied by the stationarity assumption, which is fully effective prior to and including the 1900 cross-section.

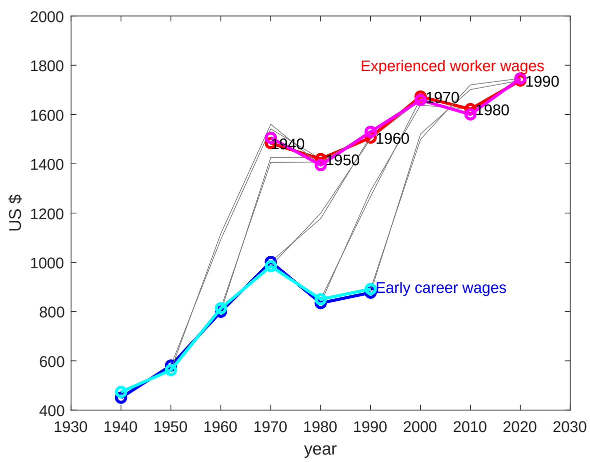
Table 7: Propagation of steady-state restrictions — After 2020

30	$y_{1990,1990+30}$	$y_{2010,2000+30}$	$y_{2010,2010+30}$	$y_{2020,2020+30}$	$y_{2020,2020+30}$
20	$y_{2000,2000+20}$	$y_{2010,2010+20}$	$y_{2020,2020+20}$	$y_{2020,2020+20}$	$y_{2020,2020+20}$
10	$y_{2010,2010+10}$	$y_{2020,2020+10}$	$y_{2020,2020+10}$	$y_{2020,2020+10}$	$y_{2020,2020+10}$
0	$y_{2020,2020}$	$y_{2020,2020}$	$y_{2020,2020}$	$y_{2020,2020}$	$y_{2020,2020}$
$\mathcal{C}$	2020	2030	2040	2050	$[2060, +\infty)$

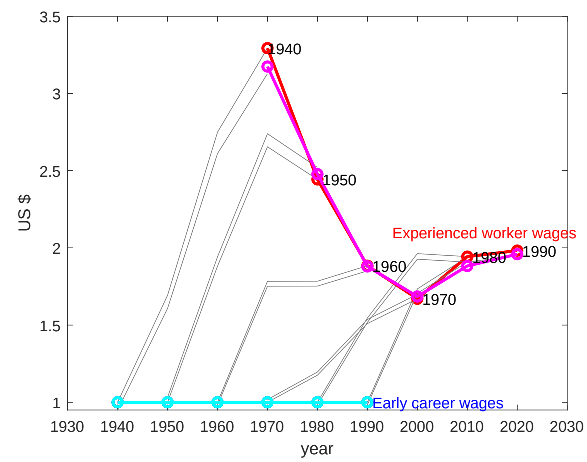
NOTE: The gray-shaded values correspond to the restrictions implied by the stationarity assumption, which is fully effective starting with the 2060 cross-section.

D Model fit: Additional results

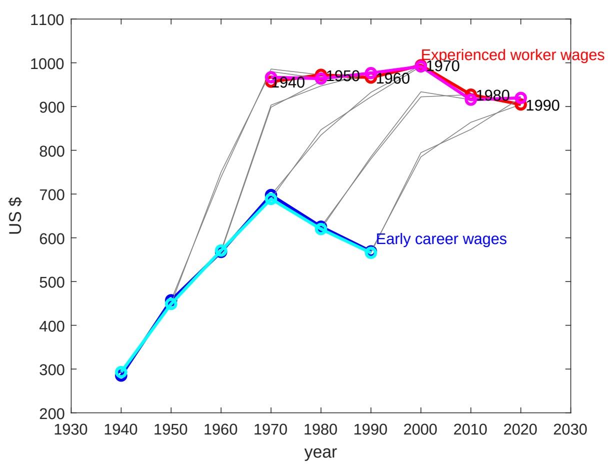
Wages $y^{z}_{a,c}$. Figure 8 shows that the model provides a good fit for wages of all cohorts, at all ages, for both unskilled and skilled workers. Given the model's good fit for wages, it also reproduces the phenomenon known as "wage flattening" – and its reversal for post-1970 cohorts, which we refer to as "wage steepening".



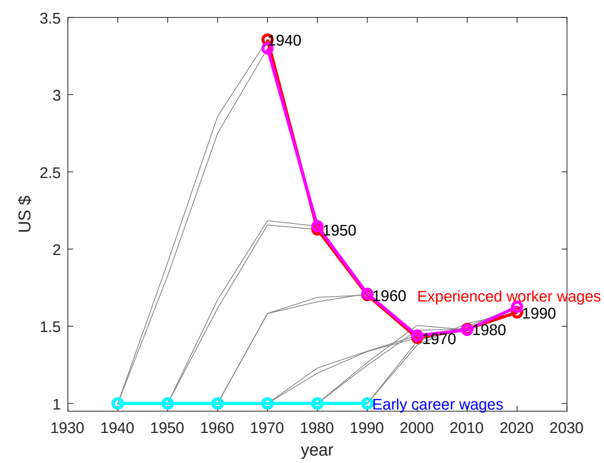
(a) Life-cycle wage - College workers



(b) Profile of life-cycle wage - College workers



(c) Life-cycle wage - Non-college workers



(d) Profile of life-cycle wage - Non-college workers

Figure 8: Wages by skill, age and cohort: Model vs. data

Source: IPUMS U.S. Census 1940-2019 and authors' own calculations. Real weekly wage (in 2010 U.S. dollars) of full-time, full-year male workers. Data: light blue for early-career wages, magenta for late-career wages. Model: blue for early-career wages, red for late-career wages.

Panel (a) of Figure 8 displays wage profiles across cohorts 1940 through 1990 for college workers. College workers entering the labor market in 1940 earn \$474 per week initially, rising to \$733 in 1950, \$1,225 in 1960, and \$1,500 in 1970 when they have 30-39 years of experience. Dividing late-career wages by early-career wages yields wage growth of 3.2-fold for the 1940 cohort, as shown in panel (b). For the 1970 cohort, college workers' wages grow by only 1.7-fold over their careers – the phenomenon the literature terms "wage flattening."

Panel (b) of Figure 8 also demonstrates that "wage steepening" better describes post-1970s workers' experiences. Wages grow 1.8-fold for the 1980 cohort and 1.9-fold for the 1990 cohort. Panel (a) suggests that wage flattening and steepening are driven primarily by rising early-career wages through the 1970 cohort, followed by declining early-career wages for subsequent cohorts.

Panels (c) and (d) of Figure 8, which display wages by age and cohort for non-college workers, show similar dynamics in life-cycle wage profiles. However, a notable difference emerges in wages for workers with 30-39 years of experience: they decline starting with the 1970 cohort for non-college workers while continuing to rise for college workers. As can be seen, non-college workers experience wage steepening because early-career wages fall even more dramatically than late-career wages.

Education choice L_c^s. Recall that in our model the distribution $\mathcal{G}(\varepsilon)$ of education costs yields the share of college workers in each cohort through: $L_c^s = \mathcal{G}(\widetilde{\varepsilon}_c) = \mathcal{G}(V_c^s - V_c^u)$. $\mathcal{G}(\varepsilon)$ is assumed to be log-normal, and the estimated parameters are $\mu_\varepsilon = 7.0583$ and $\sigma_\varepsilon = 0.7879$.

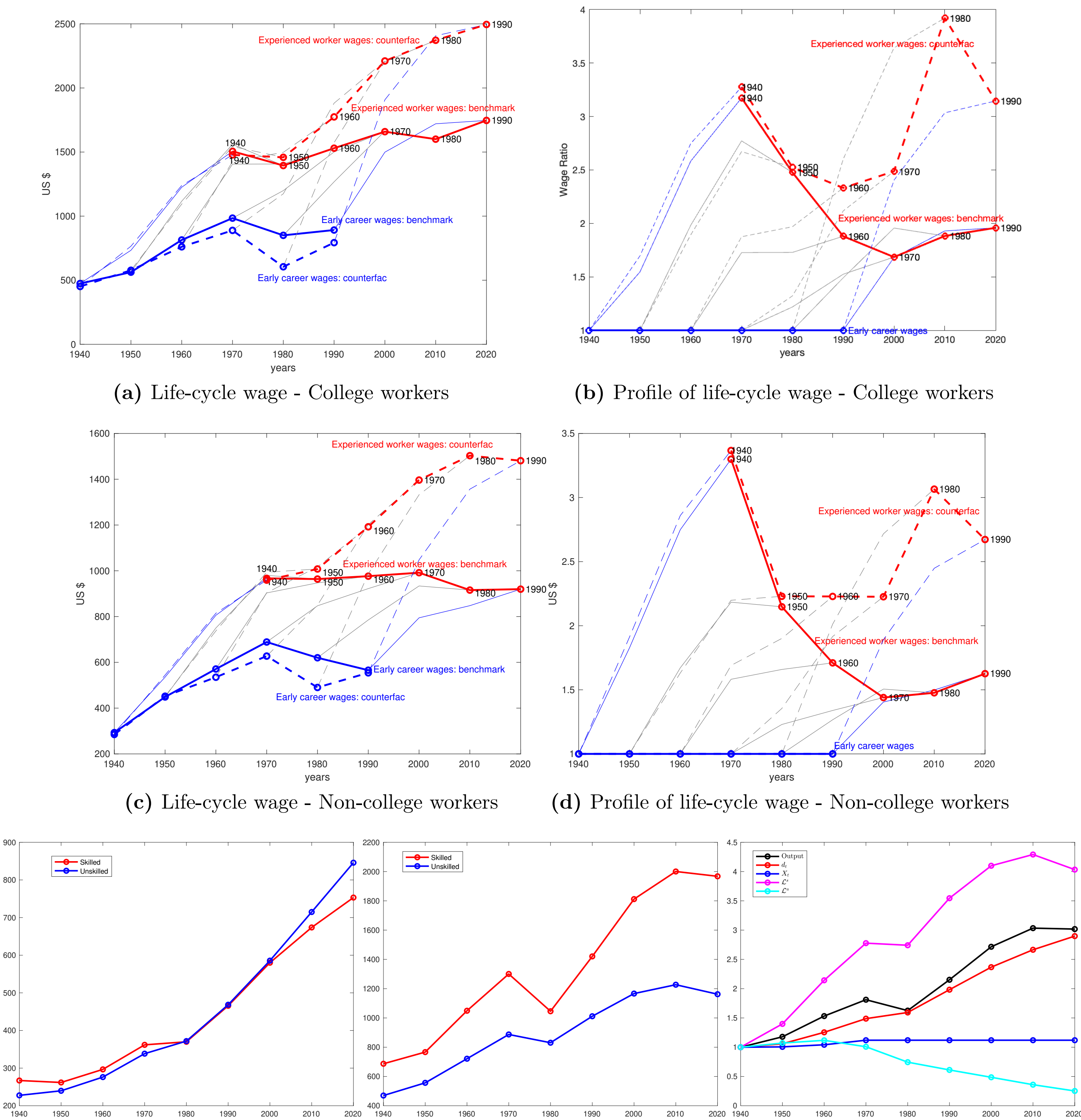
Table 8 reports the model-predicted relative supply of skilled labor among early-career workers, L_c^s. The model matches the increase in the share of skilled labor for each cohort observed in the data. Interestingly, the model captures the rapid increase in college education prior to 1990 followed by a subsequent slowdown.

Table 8: Share of college workers among young workers (L_c^s): Model vs. data

Year	1940	1950	1960	1970	1980	1990	2000	2010	2020
Data	0.2616	0.2946	0.3772	0.4146	0.5031	0.6003	0.6193	0.6383	0.6453
Model	0.2438	0.2946	0.4056	0.4259	0.4723	0.6123	0.6566	0.6407	0.6453
Diff.	-0.0178	0.0000	0.0284	0.0114	-0.0309	0.0119	0.0373	0.0023	0.0000

Source: IPUMS U.S. Census 1940-2019 and authors' own calculations. 'Diff.': difference between the model and data.

E Counterfactual experiments



(a) Life-cycle wage - College workers

(b) Profile of life-cycle wage - College workers

(c) Life-cycle wage - Non-college workers

(d) Profile of life-cycle wage - Non-college workers

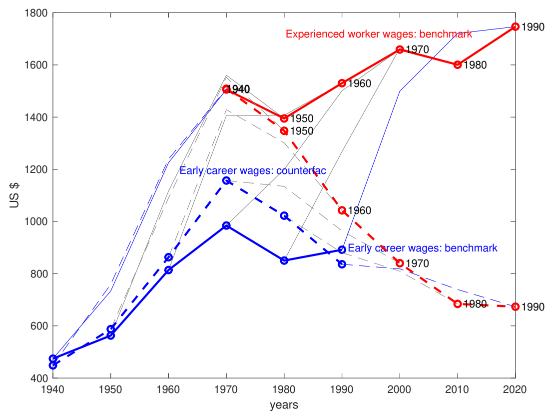
(e) Price of human capital $\{R_t^s, R_t^u\}$

(f) Wages $\{y_t^s, y_t^u\}$

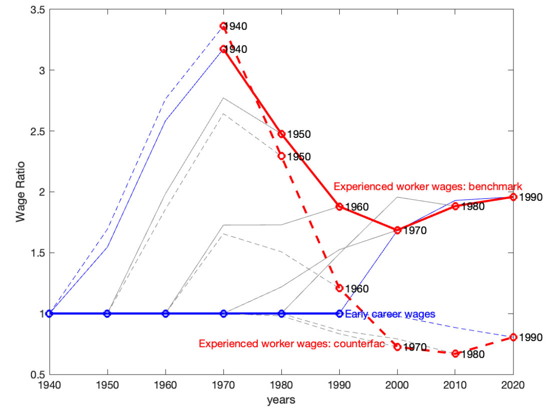
(g) Decomposition of output growth

Figure 9: Counterfactual dynamics: Holding X_t constant after 1970

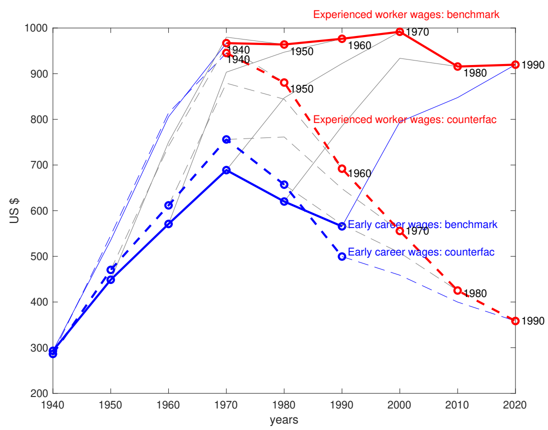
NOTE: Main model outcomes (life-cycle wages, dynamics of aggregate prices and wages, decomposition of output growth) under constant skill-neutral technological change (X_t) after 1970.



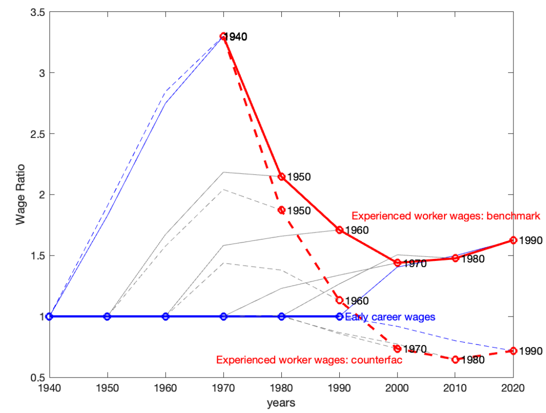
(a) Life-cycle wage - College workers



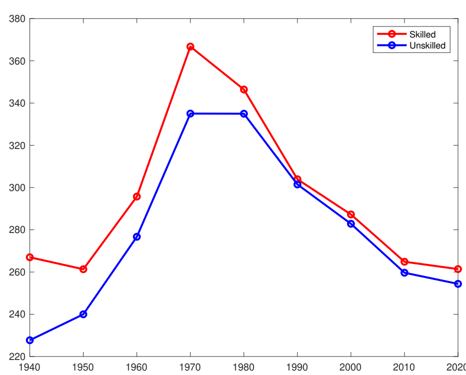
(b) Profile of life-cycle wage - College workers



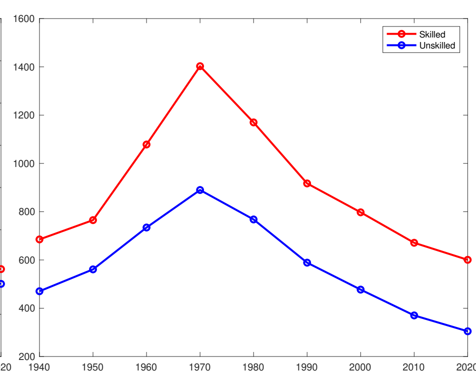
(c) Life-cycle wage - Non-college workers



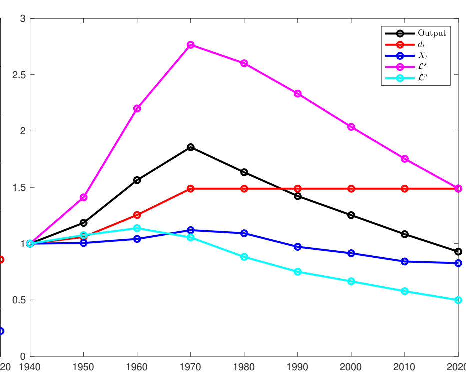
(d) Profile of life-cycle wage - Non-college workers



(e) Price of human capital $\{R_t^s, R_t^u\}$



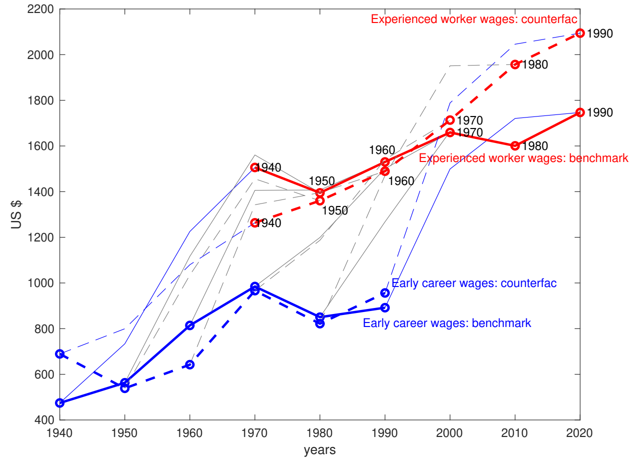
(f) Wages $\{y_t^s, y_t^u\}$



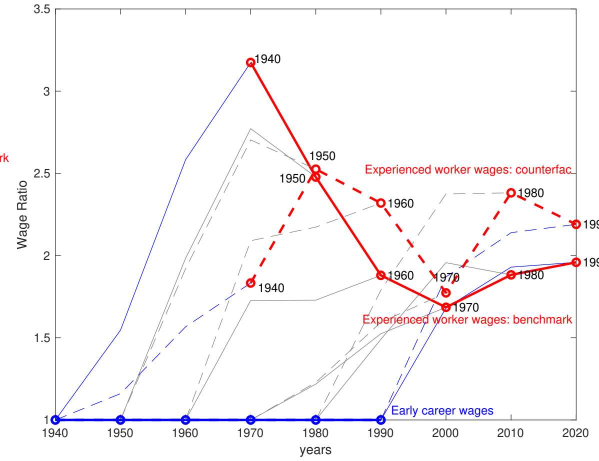
(g) Decomposition of output growth

Figure 10: Counterfactual dynamics: Holding d_t constant after 1970

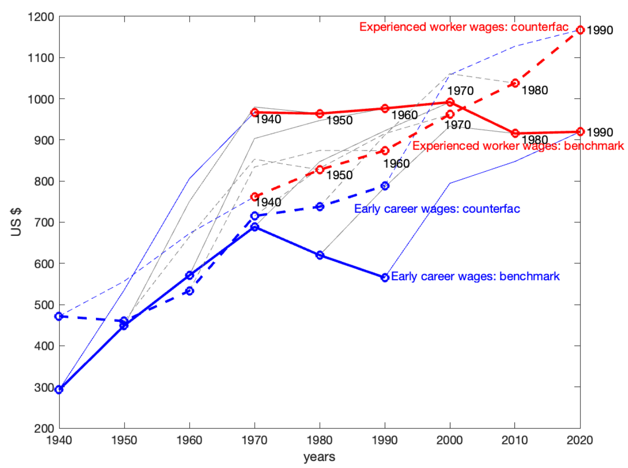
NOTE: Main model outcomes (life-cycle wages, dynamics of aggregate prices and wages, decomposition of output growth) under constant skill-biased technical change (d_t) after 1970.



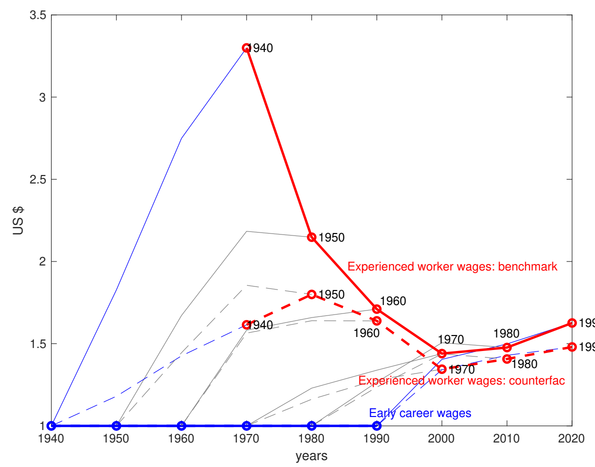
(a) Life-cycle wage - College workers



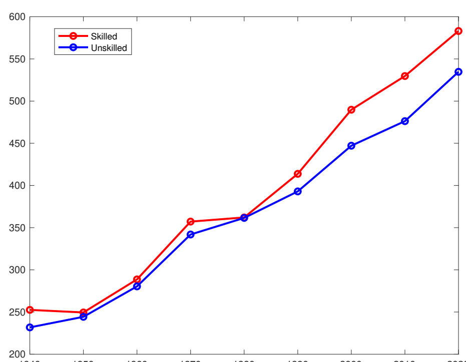
(b) Profile of life-cycle wage - College workers



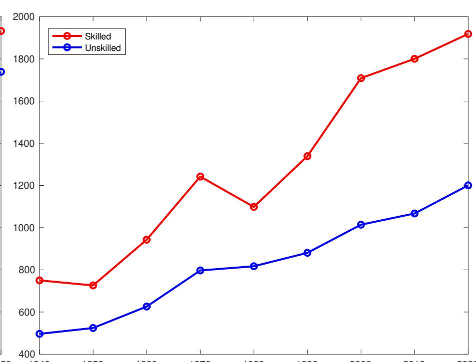
(c) Life-cycle wage - Non-college workers



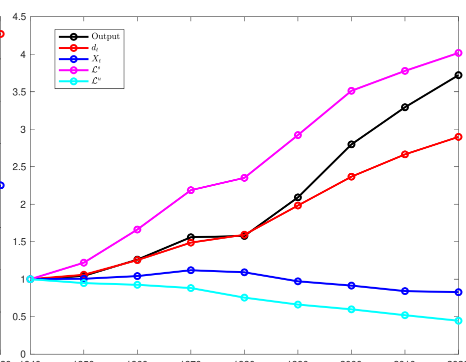
(d) Profile of life-cycle wage - Non-college workers



(e) Price of human capital $\{R_t^s, R_t^u\}$



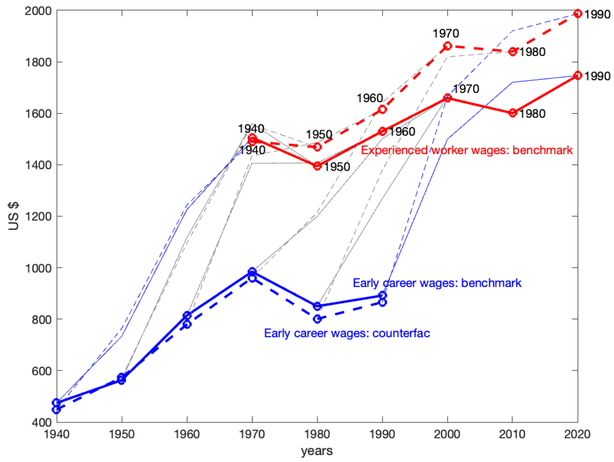
(f) Wages $\{y_t^s, y_t^u\}$



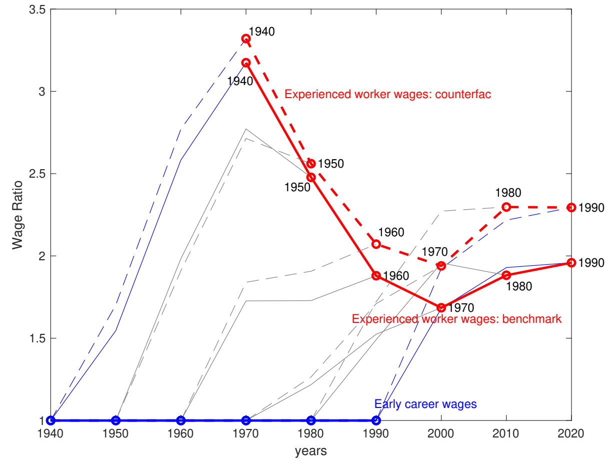
(g) Decomposition of output growth

Figure 11: Counterfactual dynamics: Holding $\{h_{0,c}^z, \alpha_c^z\}$ constant after 1970

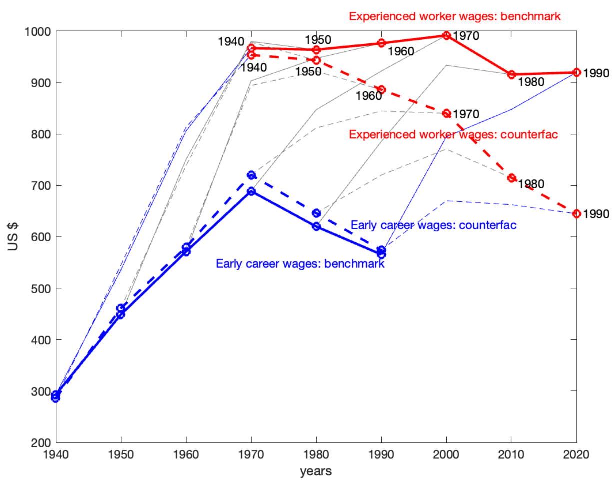
NOTE: Main model outcomes (life-cycle wages, dynamics of aggregate prices and wages, decomposition of output growth) when values of the cohort-specific human capital parameters $\{h_{0,c}^z, \alpha_c^z\}$ are held constant after 1970.



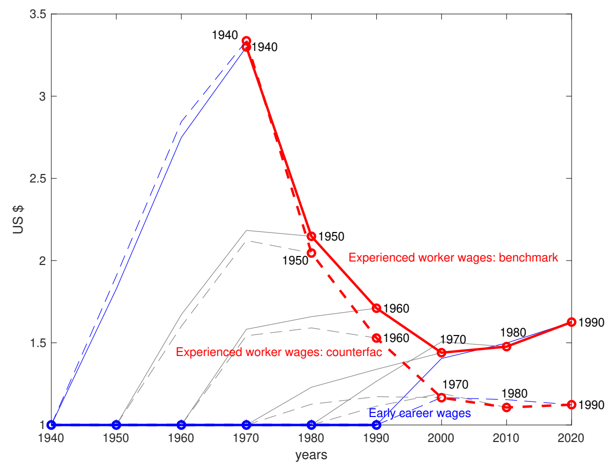
(a) Life-cycle wage - College workers



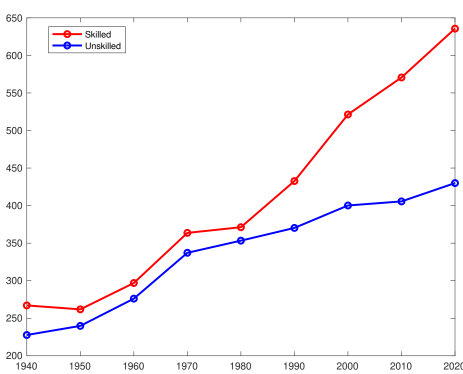
(b) Profile of life-cycle wage - College workers



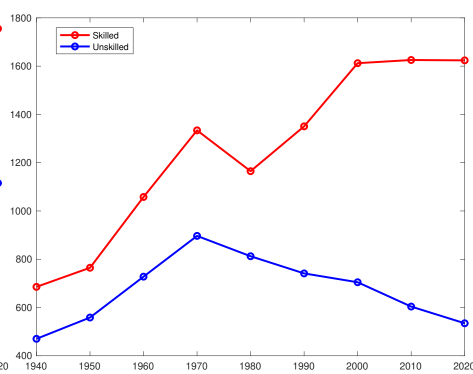
(c) Life-cycle wage - Non-college workers



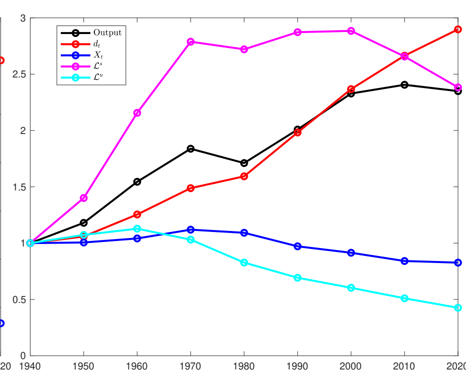
(d) Profile of life-cycle wage - Non-college workers



(e) Price of human capital $\{R_t^s, R_t^u\}$



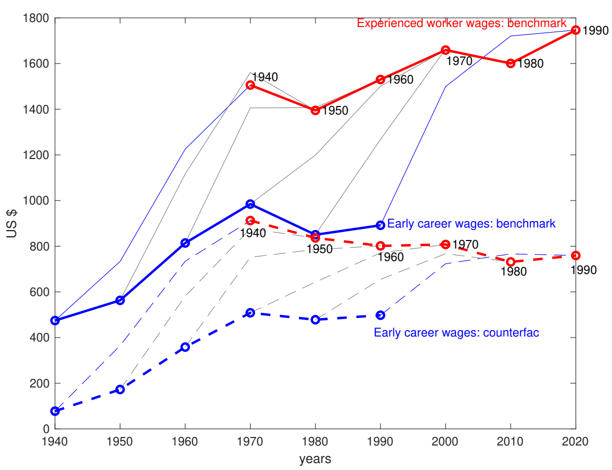
(f) Wages $\{y_t^s, y_t^u\}$



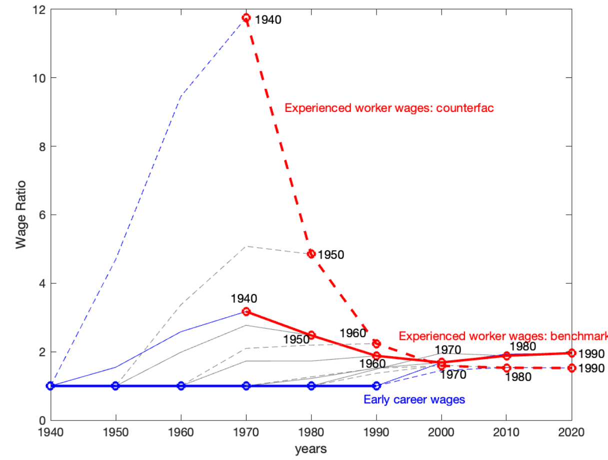
(g) Decomposition of output growth

Figure 12: Counterfactual dynamics: Holding L_t^s constant after 1970

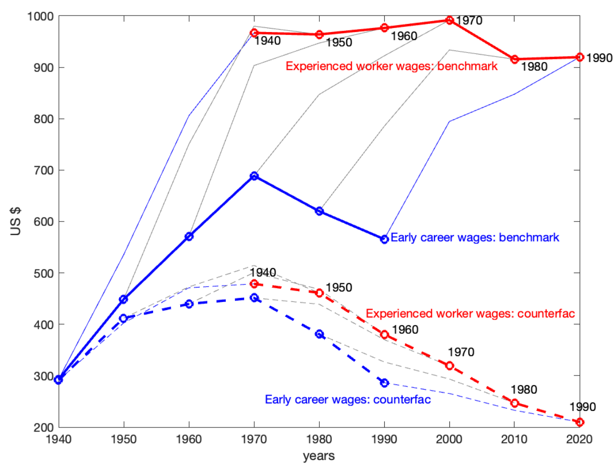
NOTE: Main model outcomes (life-cycle wages, dynamics of aggregate prices and wages, decomposition of output growth) under constant supply of young college-educated workers (L_t^s) after 1970.



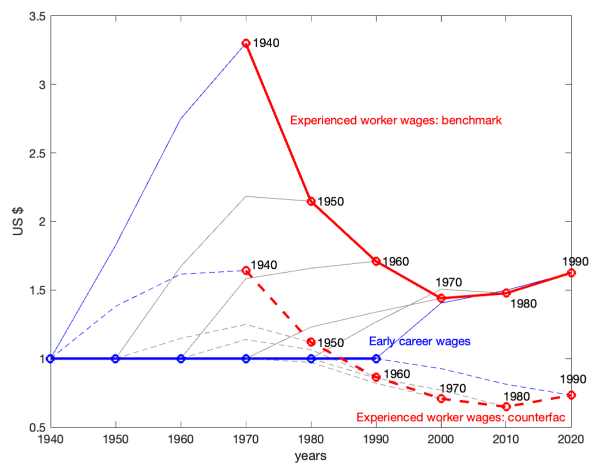
(a) Life-cycle wage - College workers



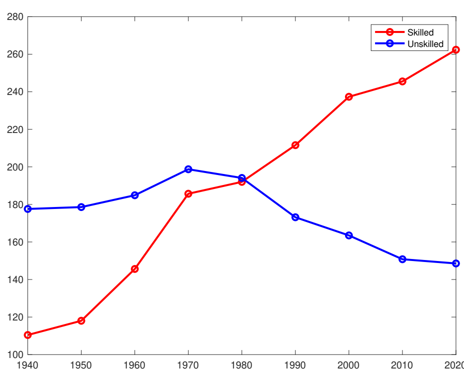
(b) Profile of life-cycle wage - College workers



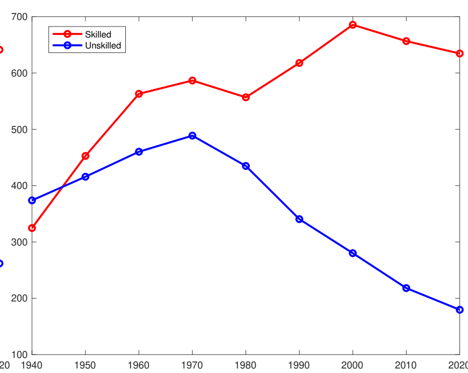
(c) Life-cycle wage - Non-college workers



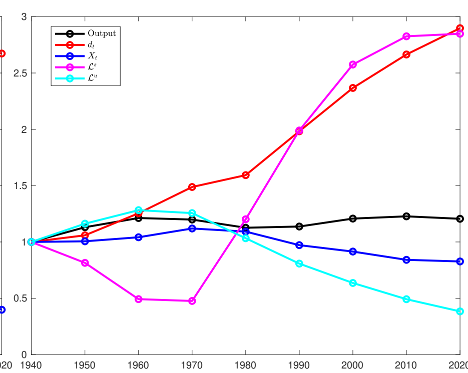
(d) Profile of life-cycle wage - Non-college workers



(e) Price of human capital $\{R_t^s, R_t^u\}$



(f) Wages $\{y_t^s, y_t^u\}$



(g) Decomposition of output growth

Figure 13: Counterfactual dynamics: Perfect skill substitutability ($\eta \to 1$)

NOTE: Main model outcomes (life-cycle wages, dynamics of aggregate prices and wages, decomposition of output growth) under the assumptions of perfect substitutability between skills.

F Model identification: Additional results

The high-dimensional nature of our macroeconomic model makes it difficult to provide a formal proof of identification. However, we can assess local identification by measuring the sensitivity of the model's moments to changes in parameter values.

Jacobian matrix. We have 105 empirical targets: 48 real weekly wages for each skill level and shares of college young workers for 9 cohorts. We first focus on the 48 cohort-specific parameters governing human capital accumulation – specifically, the parameters $h^z_{0,c}$ and α^z_c for 12 cohorts and 2 skill levels $z \in \{s, u\}$. Then we analyze the 4 parameters that are common across cohorts – the elasticity of substitution η, the curvature ζ^z, $z \in \{s, u\}$, and depreciation rate δ.

We vary each individual parameters $\theta_i = \{\theta^+_i, \theta^-_i\}$ by applying a 10% perturbation, holding others fixed at their estimated values. Each parameter change induces changes in the model's moments, denoted here as m_k with $k = 1, \ldots, 105$. We then compute the Jacobian matrix $J(\theta)$ of dimension 105×52, where each element of the Jacobian matrix represents the change in moment k divided by the change in parameter θ_i: $J(\theta_i)_k = \frac{m^+_k - m^-_k}{\theta^+_i - \theta^-_i}$. We find that the Jacobian matrix has full rank, indicating that no parameter is redundant or a linear combination of others.

Heatmaps. The heatmap in Figure 14 represents the absolute values of the elements of the Jacobian matrix for cohort-specific parameters governing human capital accumulation and wage-related moments.[29] Specifically, on the vertical axis, we report model parameters estimated for 12 cohorts from 1910 to 2020, organized as follows: Rows 1-12 show $h^s_{0,c}$ (initial human capital upon labor market entry) for skilled workers, one per cohort. Rows 13-24 show $h^u_{0,c}$ for unskilled workers. Rows 25-36 show α^s_c (returns to on-the-job training) for skilled workers. Rows 37-48 show α^u_c for unskilled workers. On the horizontal axis, we report the 96 moments corresponding to real weekly wages. The left side of the Figure displays real wages of skilled workers across 12 cohorts from 1910 to 2020, with four moments per cohort corresponding to the four life-cycle ages. The right side shows moments for unskilled workers' real wages across the same cohorts.

The Jacobian heatmap reveals a diagonal sensitivity pattern, indicating that each parameter predominantly affects moments corresponding to its associated group (skilled or unskilled of the corresponding cohort). This structure supports correct specification and local identification of the parameters. Off-diagonal elements reflect the general equilibrium

[29] To improve legibility, Figure 14 is scaled by 1,000, i.e., the figure reports $|J(\theta_i)_k|/1000$.

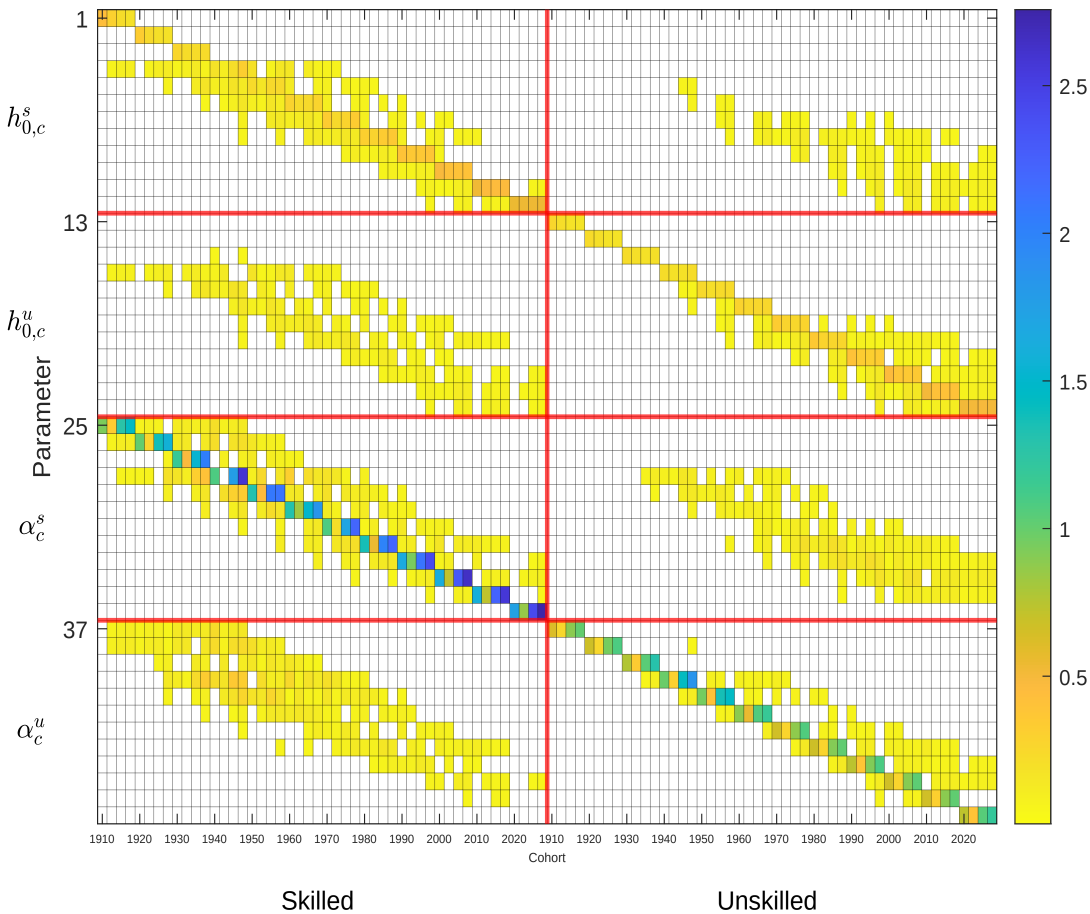


Figure 14: Jacobian matrix for cohort-specific parameters governing human capital accumulation: Moments on real weekly wages

NOTE: Absolute values of the elements of the Jacobian matrix for parameters $h^z_{0,c}$ and α^z_c, with $z \in \{s, u\}$, on the vertical axes and real weekly wage moments on the horizontal axes.

interactions embedded in the model. Since different generations interact through the production function at any given time, parameter perturbations affect not only their direct cohort-specific moments but also, to a lesser extent, moments for other workers and cohorts. The lighter intensity of these off-diagonal effects indicates that general equilibrium channels are present but do not dominate the direct identification structure, consistent with the model's intended economic mechanisms.

Next, in Figure 15 we present the absolute values of the elements of the Jacobian matrix for the same cohort-specific model parameters but we focus now on moments related to the supply of college young workers, i.e., L^s_c for cohorts $c = 1940$ through 2020. The Jacobian heatmap displays a diagonal sensitivity pattern, indicating, again, that each parameter predominantly affects the moments corresponding to its associated group (skilled or unskilled,

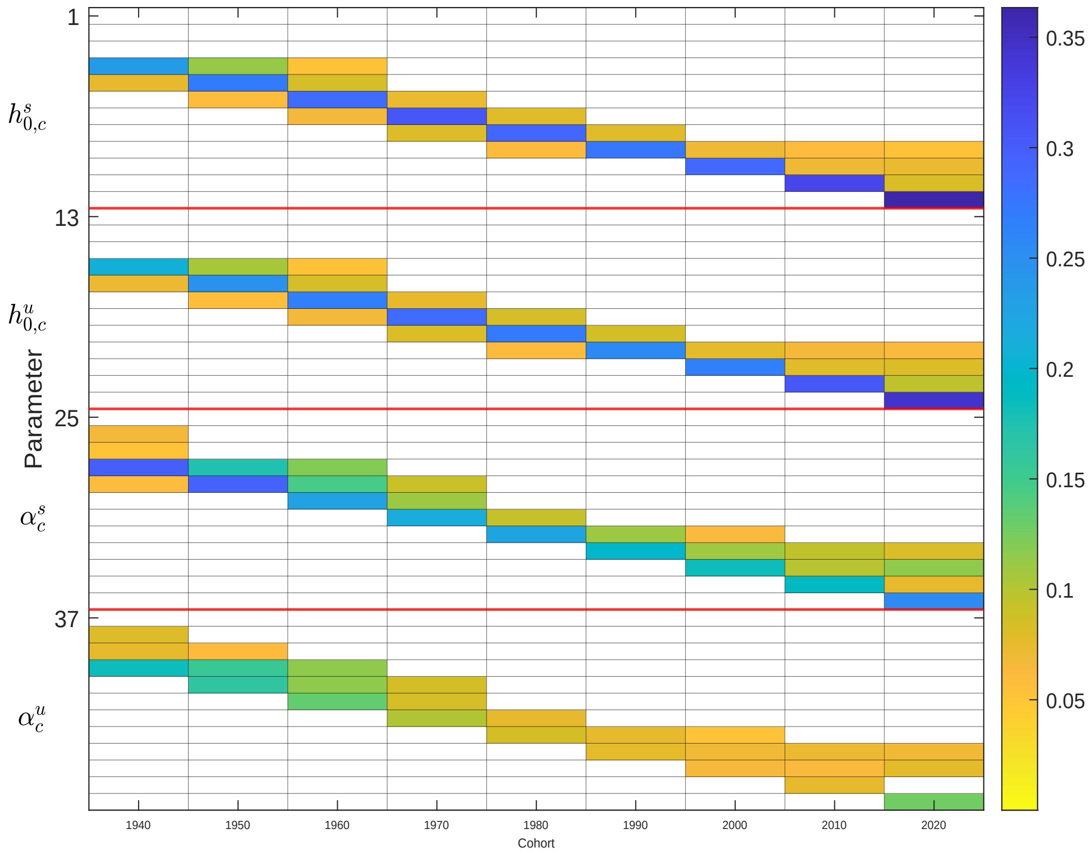


Figure 15: Jacobian matrix for cohort-specific parameters governing human capital accumulation: Share of college young workers

NOTE: Absolute values of the elements of the Jacobian matrix for parameters $h^z_{0,c}$ and α^z_c, with $z \in \{s, u\}$, on the vertical axes and shares of college young workers on the horizontal axes.

for the relevant cohort c).

Finally, Figure 16 displays the Jacobian heatmap for the parameters η, ζ^s, ζ^u, and δ. Since they are common across cohorts, we expect variations in these parameters affect all cohorts. On the horizontal axes of this Figure, we report both moments for real weekly wages (on the left side of the axes) and the shares of college young workers in each cohort (on the right-most side of the axes).

The parameter η governs the elasticity of substitution between skilled and unskilled labor in the production function. As shown in the top panel of Figure 16, it influences outcomes for all cohorts.

The parameter ζ^s affects the curvature of the human capital production function for skilled workers. As expected, changes in ζ^s have a stronger impact on empirical moments related to skilled workers. To a lesser extent, they also influence moments related to unskilled workers. This pattern is consistent with the general equilibrium interactions embedded in the

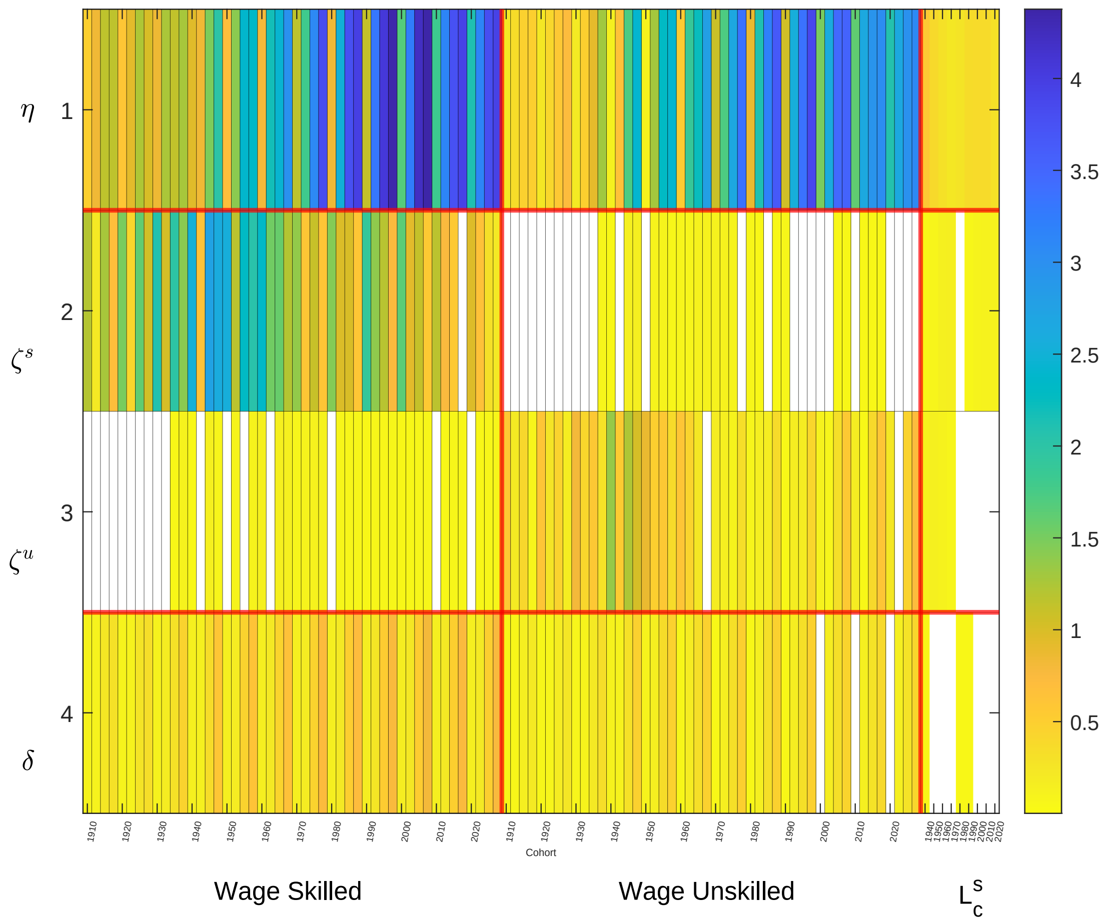


Figure 16: Jacobian matrix for the parameters governing human capital accumulation that are common across cohorts

NOTE: Absolute values of the elements of the Jacobian matrix for parameters η, ζ^s, ζ^u and δ, on the vertical axes and moments on real weekly wages and shares of college young workers on the horizontal axes.

production function, where changes in skilled labor also affect the marginal productivity of unskilled labor. Likewise, we see in Figure 16 that variations in ζ^u primarily affect moments related to unskilled workers, while also generating spillover effects on skilled worker outcomes.

The rate of human capital depreciation δ naturally affects all cohorts. Consistent with the model's economic mechanisms, its impact is stronger on wages observed later in the life cycle – as shown by the darker intensity for late-career wages of each cohort.

G The model under myopic expectations

In our model and numerical experiments, SBTC is the primary factor behind the observed evolution of the college premium, changes in the cohort-specific parameters for human capital accumulation are the most important drivers of changes in life-cycle wage profiles, and general equilibrium adjustments are key for stabilizing wage inequality. In this section, we show that these results continue to hold under the assumption of myopic behaviors.[30]

G.1 Solving the model under workers' myopic expectations

Suppose that workers hold myopic expectations regarding the dynamics of the two human capital prices R_t^z, $z \in \{s, u\}$. At time t, workers observe the current prices R_t^z and prices R_{t-10}^z that have prevailed in the recent past. They make decisions on human capital investments based on the following FOC:

$$\Omega_{a,c}^z \quad = \quad \beta \frac{R_t^z}{R_{t-10}^z} \left[1 + (1-\delta)\Omega_{a+10,c}^z\right] \quad \text{with} \quad \Omega_{30,c}^z = 0, \quad t = a + c. \tag{17}$$

Equation (17) is similar to (3) in the baseline model, but with the key difference that the expected increase in the price of human capital is assessed in a myopic fashion. Specifically, instead of $\frac{R_{t+10}^z}{R_t^z}$ (the perfect foresight scenario prevailing in Equation (3) of the baseline model), workers use $\frac{R_t^z}{R_{t-10}^z}$ (the growth rate of the price of human capital in the recent past) to assess the future value of these investments.

We solve the OLG macroeconomic model similarly to the baseline, except that workers' decisions are now based on myopic expectations (Equation (17)). In particular, the prices of human capital R_t^s and R_t^u reflect the actual stocks of aggregate units of efficient labor at time t, which may differ from workers' expectations.

G.2 Counterfactual experiments

Table 9 reports the results of counterfactual experiments under myopic expectations. It shows that the key mechanisms identified in Section 5.2 – endogenous schooling decisions and endogenous skill prices – continue to play a critical role in reducing wage inequality, even when workers are imperfectly anticipate the future path for the prices of human capital.

[30] Guvenen & Kuruscu (2010) investigate the implications of imperfect foresight and Bayesian learning in a Ben-Porath model of labor earnings with rich dimensions of worker heterogeneity. They find that their result regarding the response of the college wage premium to SBTC is not critically dependent on the assumption of perfect foresight.

Table 9: Counterfactual experiments under myopic expectations

College premium				
Year	1940	1970	1990	2020
Baseline	1.46	1.49	1.51	1.93
Fixed L_c^s	1.48	1.47	1.76	3.06
Fixed R_t^z, $z \in \{s, u\}$	0.84	0.82	1.67	3.55
Lifetime wage growth				
Cohort	1940	1970	1990	
Unskilled workers				
Baseline	3.35	1.42	1.58	
Fixed L_c^s	2.00	1.53	1.08	
Fixed R_t^z, $z \in \{s, u\}$	1.53	0.86	0.64	
Skilled workers				
Baseline	3.29	1.67	1.98	
Fixed L_c^s	1.72	2.28	2.80	
Fixed R_t^z, $z \in \{s, u\}$	2.36	2.69	1.67	

NOTE: Model outcomes (college premium and lifetime wage growth) under myopic expectations. 'Baseline' presents model outcomes with the full dynamics coming from aggregate and cohort-specific shocks and responses. The rest of the table presents model outcomes where either aggregate or cohort-specific responses are held constant to their estimated value(s) in 1970.

College premium. When the supply of skilled labor, L_t^s, is held fixed at its 1970 level, the college premium rises much more steeply than in the baseline experiments, reaching 3.06 in 2020 (Table 9). Similarly, when the prices of human capital R_t^z are held constant (instead of adjusting endogenously, as in the baseline model), the college premium reaches an even higher level of 3.55 in 2020 (vs. 1.93 in baseline). These counterfactual results confirm that both endogenous education and price adjustments play a major role in dampening the rise of the college wage premium.

Lifetime wage growth. In Table 9, we observe the same stabilizing role of endogenous mechanisms for the behavior of lifetime wage growth profiles.

Under myopic expectations, wages at the end of a worker's career are 58% higher than early-career wages for unskilled individuals from the 1990 cohort. When skilled labor supply is held fixed at its 1970 level, the 1990 cohort's life-cycle wage growth falls to 1.08. Under exogenous skill prices, it declines further to 0.64 – a dramatic decline illustrating the importance of general equilibrium adjustments.

For skilled workers, the life-cycle growth rate of wages is 1.98 for the 1990 cohort. Fixing education at the 1970 level leads to a steeper profile for this cohort (a 2.80 growth rate), while exogenous skill prices reduces the growth rate to 1.67, showing that price feedbacks are essential in moderating the trajectory of skilled wage growth.

H Including women

In this section, we report how the results change when full-time, full-year female workers are also included in the sample of our analysis. Most of our main result continue to hold.

H.1 Stylized facts and model fit

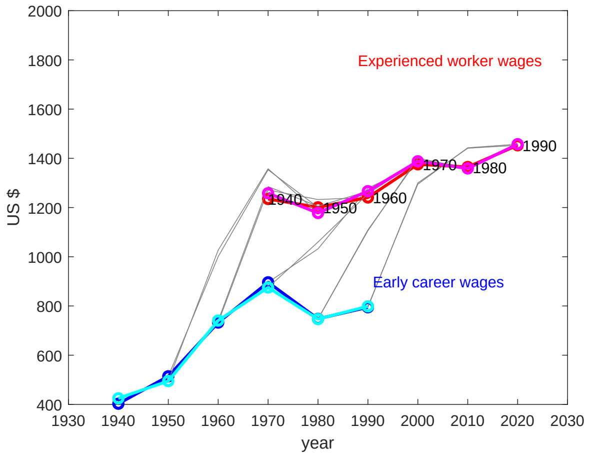
Figure 17 displays life-cycle wage profiles by education group based on the broader sample with both men and women. As expected, the inclusion of women in the sample leads to lower observed wage levels, reflecting gender differences in hours worked, differences in occupations, and possibly other due to other factors driving the gender wage gap. Despite the differences in wage levels, the key qualitative patterns shown in Figure 8 of the main text are also present in Figure 17: life-cycle wage profiles become flatter for the successive cohorts entering the market after 1940, and then become steeper for the post-1970 cohorts. This observation reinforces the conclusion that the flattening/steepening pattern is a fundamental feature of U.S. wage dynamics in the post-WWII era.

Figure 18 shows that the model continues to replicate the key empirical patterns when the sample includes both men and women. In Panel (a), the model matches the double dip in the college premium (notably in 1950 and 1970) as well as the sharp increase after 1980, consistent with the dynamics shown in Figure 2 of the main text based on the sample with male workers only. Panel (b) reports the evolution of overall wage inequality (coefficient of variation). Although the levels are again lower in the model compared to the data (reflecting the limited degrees of worker heterogeneity included in the model), it reproduces the broad V-shape behavior of inequality over time, including the stagnation in the 1970s and the upward trend in recent decades. In sum, the model calibrated to data that includes both men and women remains consistent with the key qualitative patterns characterizing between-group wage inequality (the college premium) and overall wage dispersion.

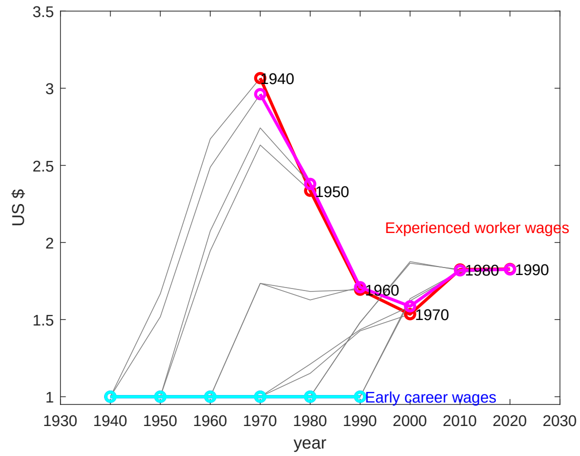
H.2 Estimated parameters

Table 10 reports the estimated parameter values for the analysis that includes male and female workers. They are essentially similar to the baseline parameter values. The elasticity of substitution between skilled and unskilled workers is somewhat higher yet not too far from that in the main text, namely 2.63 vs. 2.06 in our baseline analysis.

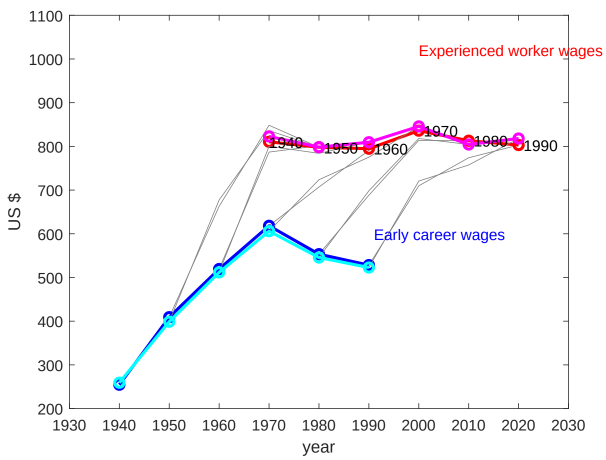
Figure 19 reports the estimated cohort-specific parameters for human capital accumulation when the sample analyzed includes both men and women. The estimated values closely mirror the baseline results shown in Figure 4. Human capital parameters vary significantly



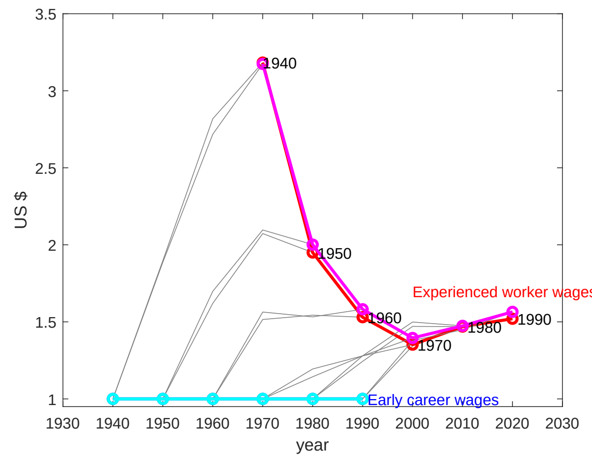
(a) Life-cycle wage - College workers



(b) Profile of life-cycle wage - College workers



(c) Life-cycle wage - Non-college workers



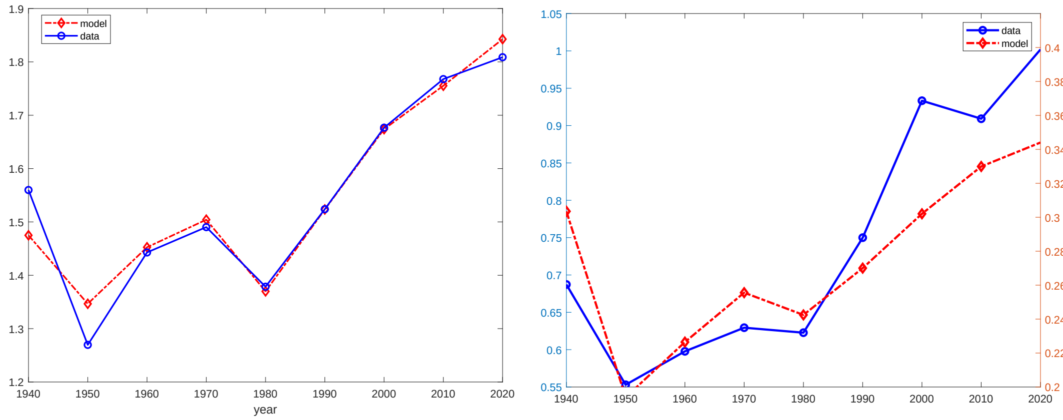
(d) Profile of life-cycle wage - Non-college workers

Figure 17: Wages by skill, age and cohort (including women): Model vs. data

NOTE: IPUMS U.S. Census 1940-2019 and authors' own calculations. Real weekly wage (in 2010 U.S. dollars) of full-time, full-year male and female workers. Data: light blue for early-career wages, magenta for late-career wages. Model: blue for early-career wages, red for late-career wages.

across cohorts, with a hump-shaped profile for the endowments in human capital upon entry and a declining trend in the learning ability parameters, particularly for unskilled workers. As in the baseline analysis, we observe a persistent asymmetry in favor of skilled workers, who enter the labor market with higher initial endowments in human capital throughout.

Next, Figure 20 displays the paths of the two aggregate shocks X_t and d_t for the model estimated on the broader sample with the two gender groups. Their dynamics are similar to those displayed on Figure 5 in the main text. In Figure **??**, we also see that that the relative price of skills, R_t^s/R_t^u, remains relatively stable over time, consistent with our baseline



(a) College premium **(b)** Changes in overall wage inequality

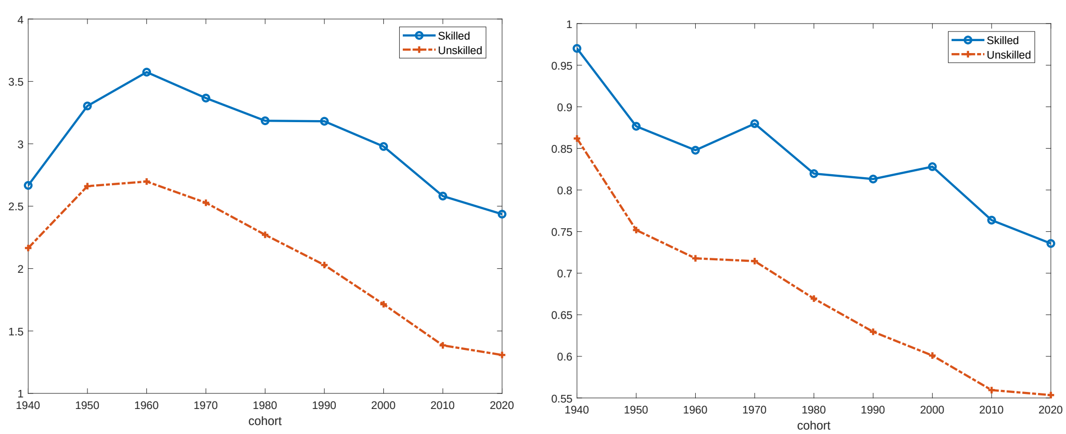
Figure 18: College premium and overall wage inequality (including women): Model vs. data

NOTE: IPUMS U.S. Census 1940-2019 and authors' own calculations. Real weekly wage (in 2010 U.S. dollars) of full-time, full-year male and female workers. Data: solid lines. Model: dashed lines.

Table 10: Common parameter values (including women)

Parameters		Value
δ	Human capital depreciation rate	10%
ζ^s	Curvature of human capital prod. function $(eh)^{\zeta^s}$, skilled	0.75
ζ^u	Curvature of human capital prod. function $(eh)^{\zeta^u}$, unskilled	0.75
η	Elasticity of substitution between skilled and unskilled $\frac{1}{1-\eta}$	2.63

NOTE: Values of parameters shared across cohorts for the model estimated on the broader male and female sample.

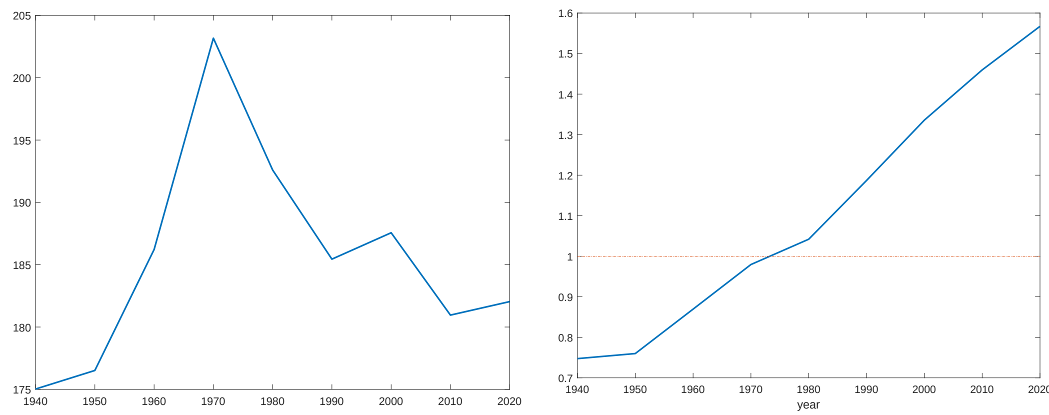


(a) Initial human capital endowments $h^z_{0,c}$ **(b)** Ability to learn α^z_c

Figure 19: Cohort-specific parameter values $\{\alpha^z_c, h^z_{0,c}\}^{2020}_{c=1940}$, $z \in \{s, u\}$ (incl. women)

NOTE: Values of cohort-specific parameters for the model estimated on the broader male and female sample.

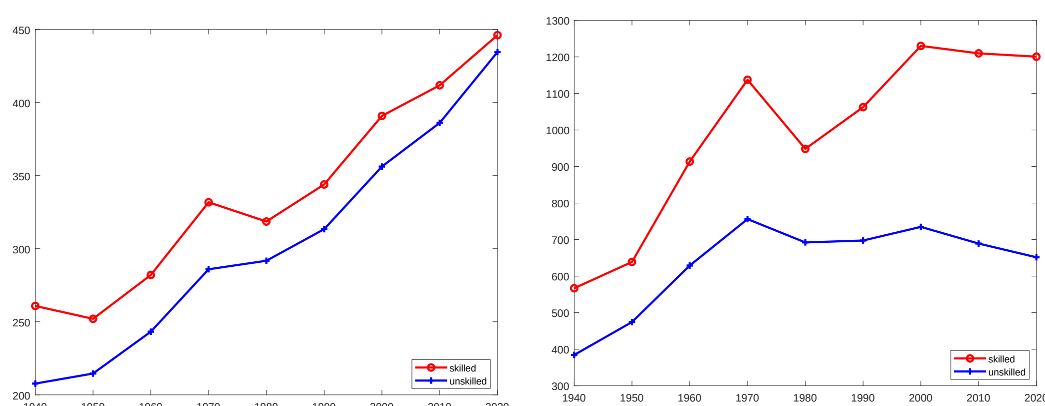
findings (Figure 6 in the main text). Given the widening gap in average wages between skilled and unskilled workers, this stability in relative prices implies a substantial increase in relative labor efficiency. This interpretation reinforces one of the core messages of the baseline model: wage inequality is primarily driven by changes in the quality (rather than the price) of labor.



(a) Skill-neutral technological progress X_t **(b)** Skill-biased technological progress d_t

Figure 20: Aggregate shocks (when including women)

NOTE: Aggregate shocks of skill-neutral and skill-biased technological change in the model estimated on the broader male and female sample.



(a) Price of human capital $\{R_t^s; R_t^u\}$ **(b)** Average wages $\{Y_t^s; Y_t^u\}$

Figure 21: Price of human capital and average wages (including women)

NOTE: Price of human capital and average wages in the model estimated on the broader male and female sample.

H.3 Robustness of main results

Table 11 reports the results of counterfactual experiments from the model based on the broader male and female sample.

Table 11: Counterfactual experiments (including women)

College premium				
Year	1940	1970	1990	2020
Baseline	1.47	1.50	1.52	1.84
Fixed L_c^s	1.47	1.49	1.77	2.78
Fixed R_t^z, $z \in \{s, u\}$	1.06	1.10	1.62	2.93
Lifetime wage growth				
Cohort	1940	1970	1990	
Unskilled workers				
Baseline	3.18	1.35	1.52	
Fixed L_c^s	3.16	1.14	1.15	
Fixed R_t^z, $z \in \{s, u\}$	2.00	0.86	0.89	
Skilled workers				
Baseline	3.07	1.54	1.83	
Fixed L_c^s	3.10	1.77	2.07	
Fixed R_t^z, $z \in \{s, u\}$	7.25	1.80	1.83	

NOTE: Model outcomes (college premium and lifetime wage growth) estimated on the broader male and female sample. 'Baseline' presents model outcomes with the full dynamics coming from aggregate and cohort-specific shocks and responses. The rest of the table presents model outcomes where either aggregate or cohort-specific responses are held constant to their estimated value(s) in 1970.

College premium. When the supply of skilled labor is fixed at its 1970 level, the college premium reaches 2.78 in 2020, compared to 1.84 in the baseline analysis restricted to male workers. When we hold the prices of skills R_t^z fixed at their 1970 levels, the college premium rises even further to 2.93. These results reiterate the finding that endogenous responses in both education and prices significantly reduce wage inequality.

Lifetime wage growth. In Table 11, we find that the lifetime growth rate of wages is 1.52 for unskilled workers from the 1990 cohort, according to the model estimated with data from the male and female sample. This growth is significantly reduced when the supply of college young worker is held constant at its 1970 level (1.15), and it even drops below one (0.89) under exogenous skill prices.

For skilled workers, the life-cycle growth rates of wages is 3.07 for the 1940 cohort and 1.83 for the 1990 cohort. When the share of college-educated workers among young individuals is held constant after 1970, the wage profile becomes steeper for the 1990 cohort (2.07), while holding skill prices fixed to their 1970 values reduces life-cycle growth rates to 1.83.

In sum, the lifetime wage profiles of non-college workers experience strong (counterfactual) flattening for recent cohorts when general equilibrium effects are suppressed. For college-educated workers, price responses play a key role in shaping lifecycle profile of wages and, notably, in generating wage steepening among recent cohorts of workers.