Technological Change and Earnings Inequality in the U.S.: Implications for Optimal Taxation*

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Abstract

Since 1980 there has been a steady increase in earnings inequality alongside rapid technological growth in the U.S. economy. To what extent does technological change explain the observed increase in earnings dispersion? How does it affect the optimal progressivity of the tax system? To answer these questions, we develop a life-cycle, overlapping generations model with uninsurable idiosyncratic earnings risk, multiple sources of technological change, a detailed tax system, and occupational choice. Calibrating the model to the U.S. we find that occupation-biased technological change can account for three quarters of the increase in post-tax earnings Gini. The main driver is the rising relative wage of non-routine cognitive occupations, which benefit the most from complementarity with capital. However, we show that non-routine manual occupations, which have the lowest average wage, also benefited from technological progress relative to routine occupations, which occupy the center of the wage distribution. For this reason, optimal progressivity drops from 1980 to 2015, as lower paid occupations are relatively better off as a result of technological change.

Keywords: Income Inequality, Taxation, Technological Change, Automation

JEL Classification: E21; H21; J31.

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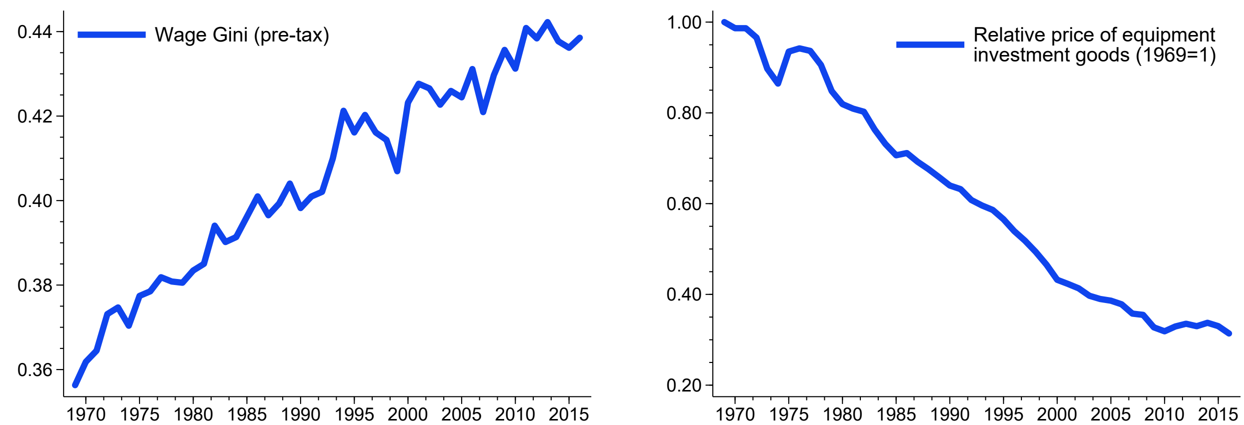
1 Introduction

Earnings dispersion in the U.S. has steadily increased at least since 1980. Figure 1 shows that this phenomenon occurred in tandem with a fall in the relative price of equipment investment goods, for example, which can be viewed as reflecting investment-specific technological change (Krusell et al., 2000; Karabarbounis and Neiman, 2014), such as cheaper access to computing power and storage. In this paper, we answer the following questions: (i) to what extent does technological change explain the observed increase in earnings dispersion? (ii) how does it affect the optimal progressivity of the tax and transfer system?

To answer these questions, we design an overlapping generations model featuring uninsurable idiosyncratic earnings risk, multiple sources of technological change, a detailed tax system, and occupational choice. Households choose an occupation at the start of their work lives based on an idiosyncratic cost of acquiring the necessary skills and on the distribution of future earnings. Occupations differ in terms of the nature of the tasks that are being performed, in the spirit of Autor et al. (2003): Non-routine cognitive (NRC), non-routine manual (NRM), routine cognitive (RC) and routine manual (RM).

The extent to which labor demand and wages for each of these occupation categories will affect the wage distribution is determined by their respective roles in the production function, by latent skill-biased technological change, and, in particular, by their complementarity with capital equipment. In simple terms: The fall in the price of equipment investment goods spurs capital accumulation and creates a demand by firms for workers in occupations with tasks which are more complementary with capital relative to those that are less so. If there are barriers to mobility between occupations and different costs of entry, the rise in labor demand creates a wage premium for workers in those occupations. In our model, barriers to mobility are modeled as an idiosyncratic cost of acquiring the necessary skills at labor market entry, with no additional mobility allowed during household's work life.



(a) Inequality

(b) Investment-specific technological change

Note: The pre-tax earnings Gini is computed from the CPS for employed workers. Description of the sample is provided on section 2. The relative price of investment is computed as the ratio between equipment investment prices from the BEA and the BLS urban consumer price index.

Figure 1: Inequality and ISTC.

We find that occupation-biased technological change can account for 90% of the increase in post-tax earnings Gini. The main driver is the rising relative wage of non-routine cognitive occupations, which benefit the most from complementarity with capital. However, we show that non-routine manual occupations, which have the lowest average wage, have also benefited from technological progress relative to routine occupations, which occupy the center of the wage distribution. For this reason, we find that optimal progressivity drops from 1980 to 2015, as lower paid occupations are relatively better off.

Literature. This paper is related to the literature which investigates the impact of technological change on inequality. Our first contribution is to expand on the seminal paper by Krusell et al. (2000), who document the role of skill-biased technological change and capital-skill complementarity in the skill premium, by specifying and estimating an aggregate production function with labor inputs based on occupations rather than the levels of education of the workforce. To do this, we use the occupation taxonomy of Autor et al. (2003), who study the effect of computerization on changes in employment by occupation categories. They posit that some occupations have a prevalence of tasks which involve complex problem-solving and interaction (so-called non-routine tasks) which are very costly or nigh impossible to automate using a pre-defined set of instructions. We use the cross-walk developed by Cortes et al. (2020) to map tasks into occupation codes, in order to calculate equilibrium quantities of labor input by occupation category. Eden and Gaggl (2018) also estimate an aggregate production function for the U.S. using the routine/non-routine paradigm and investigate the welfare implications of investment-specific technological change for the welfare of a representative agent. In contrast, our work uses the four task dimensions postulated by Autor et al. (2003) and also allows for labor-augmenting technological change at the occupation level, which are important for our conclusion that workers at the bottom of the distribution have enjoyed wage growth relative to the center of the wage distribution as a result of technological change. While our model draws heavily on the task-based framework used in the literature (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, Moll et al., 2019) we do not model tasks explicitly. We thus forego a more detailed characterization of the production process in favor of the ability to measure inputs more accurately, enabling the estimation a more abstract version of the production technology.

This paper is also related to the literature on optimal taxation. Our contribution is to assess the impact of technological change on optimal progressivity in an incomplete markets model with occupational choice. This is similar to the focus of the recent work by Guerreiro et al. (2021), who study capital taxation in a model with the possibility of automation of tasks, and endogenous skill/occupation choice. Our contribution is distinct from theirs in that we broaden the analysis to include the cognitive/manual dimensions of tasks, and focus on the progressivity of the labor income tax schedule. Like them, however, we assume that older generations cannot change occupations, which is in line with the evidence provided by Cortes et al. (2020), who argue that the fall in routine employment in the U.S. has been primarily caused by declining inflow rates among younger workers. The closest paper to our own is Heathcote et al. (2020), who study the impact of technological change on optimal progressivity in an incomplete markets model with occupational choice. However, their focus is on college education and skill-biased technological change, while our paper takes an occupation-based approach.

To dilute the perceived social cost of these trends several policies have been suggested, including a proposal famously put forth by Bill Gates to tax robots and "even slow down the speed [of automation]" (Delaney, 2017). The issue of optimal capital taxation has been discussed extensively since the seminal papers by Chamley (1986) and Lucas (1990), who find that the the optimal rate of capital taxation is zero in the steady state. In contrast, Aiyagari (1995), using an incomplete markets model with borrowing constraints, determines that the optimal income tax on capital income is positive, even in the long run.

The rest of the paper is organized as follows. In Section 2, we discuss the stylized facts that underlie our modeling choice. In Section 3, we describe the model. In Section C we discuss the results from production function estimation. In Section 5, we show the calibration strategy. In Section 6, results are presented. Section 7 concludes.

2 Data

Our analysis of the U.S. labor market is carried out along the two dimensions proposed by Autor et al. (2003) to classify occupations: (i) whether the main tasks are more susceptible to automation (routine) or less (non-routine); and (ii) the nature of the tasks involved, i.e., whether they are predominantly cognitive or manual. This classification system yields four mutually exclusive occupation groups: non-routine cognitive (NRC), non-routine manual (NRC), routine cognitive (RC) workers and routine manual (RM). We use data from the Census Bureau Current Population Survey (CPS), spanning the period from 1968 to 2016, to study how quantities and prices have changed since the late

1960s for each of these groups.

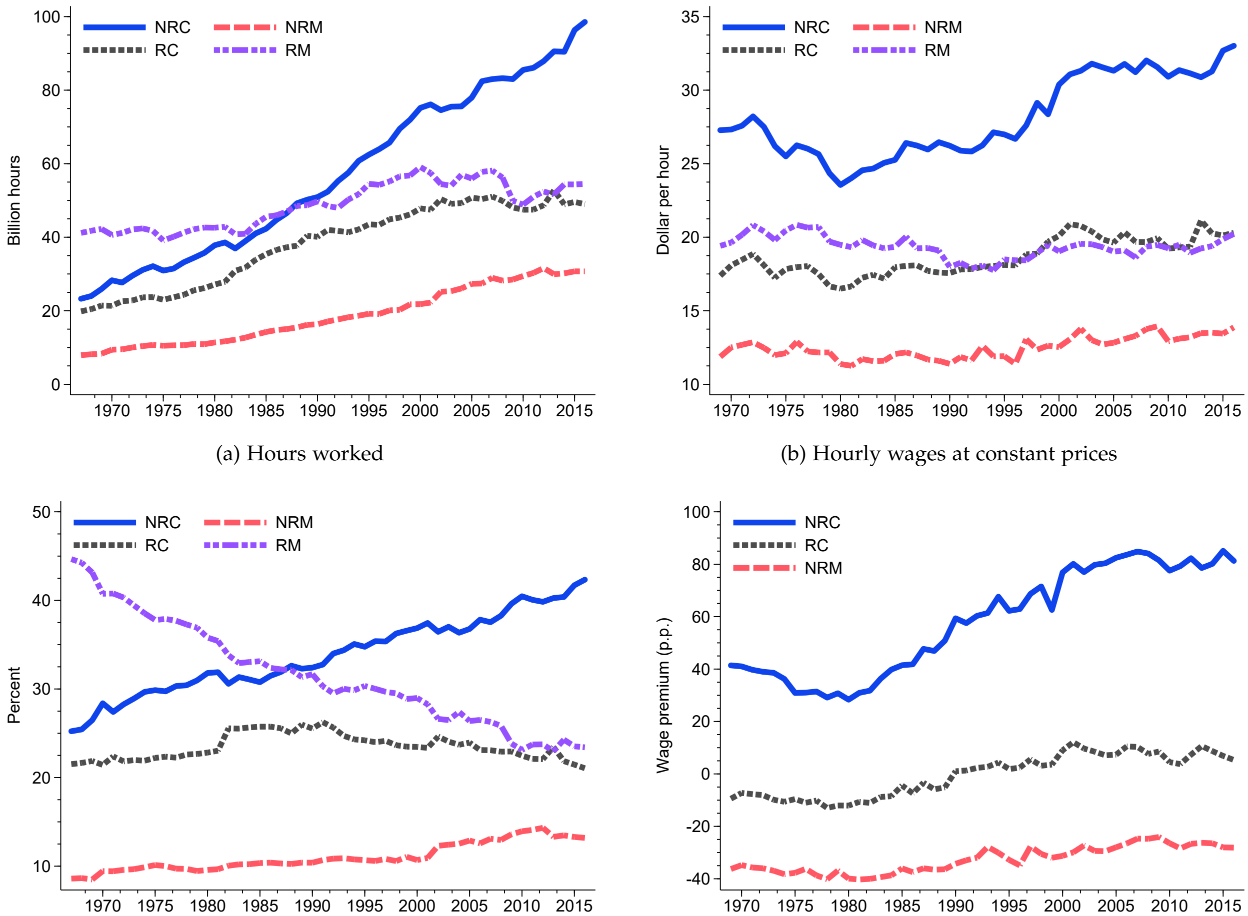
We use the Annual Social and Economic Supplement (ASEC) from the March CPS survey available from Flood et al. (2018), which contains data on yearly earnings and hours worked in the previous calendar year. The CPS employs the US Census Bureau 2010 occupation classification system, and we use the cross-walk table of Cortes et al. (2020) to categorize each worker into one of the aforementioned classes. This cross-walk is based on the so-called "consensus" classification scheme of Acemoglu and Autor (2011). The population of interest is the set of non-military, non-institutionalized individuals aged 16 to 70, excluding the self-employed and farm sector workers. See Appendix A for additional details on data treatment. These data are used to construct time series on employment and wages by occupation category. To calculate wage premia we use the method of Krusell et al. (2000), as described in Appendix B.

Figure 2 shows the evolution of employment and wages for the selected occupation categories. From 1968 to 2016, hours worked increased roughly five-fold in the NRC category, three-fold in NRM, doubled in RC, and nearly stagnated in RM.

There are three main takeaways: (i) the strong performance of NRC workers compared to other groups and, in particular, to RM workers; (ii) the growth of cognitive worker groups relative to manual; (iii) the rise of non-routine cognitive wage premium.

The central hypothesis in this paper is that one of the main drivers of the increase in inequality since the 1980s has been the discriminating effect that investment specific technological change has had on these four groups due to its diverse interaction with each labor variety. This reasoning is similar to that of Krusell et al. (2000), Karabarbounis and Neiman (2014), Acemoglu and Restrepo (2017), and Eden and Gaggl (2018).

This choice was made due to the quantitative importance of ISTC for the long-run growth of output per hours worked in the U.S. economy, originally estimated to be 60% in Greenwood et al. (1997), as well as its potential to disrupt labor market conditions. Indeed, Krusell et al. (2000) used a model of capital-skill complementarity and ISTC



(a) Hours worked

(b) Hourly wages at constant prices

(c) Share of hours worked

(d) Wage premia

Note: Wage premia are obtained as the log difference between the constant composition average wage of each occupation category. Groups for wages are constructed with using a constant composition of individual observable characteristics (experience, education, etc).

Figure 2: Employment and wages by occupation category.

to study the increased wage dispersion in the U.S economy and are able to track the progress of the skill premium. Similarly to Acemoglu and Restrepo (2017) and Eden and Gaggl (2018), we view the process of ISTC as akin to increased automation of routine tasks in the economy. However, we focus on the wage premium rather than on worker displacement in this paper.

Central to investment-specific technological change are the falling prices of capital goods, which can be interpreted as evidence of increasing productivity in the investment goods sector. As an illustration of this interpretation, consider that in the 1950s a computer was leased for 200,000 per month in inflation-adjusted 2010 dollars, plus the costs of the staff and energy required to operate it.[1] Today, any computer or smartphone equipped with microprocessors costs a fraction of that price and is able to deliver a processing speed which is many million times that of a large-scale computer in the 1950s.[2] To get a sense of the scale of technological change, the CPU of a Play Station 2 is 1,500 times faster than the guidance computer on Apollo 11, while the Apple iPhone4 is 4,000 times faster.

Is there reason to believe that this source of growth has a uniform impact across labor markets? Krusell et al. (2000) argue that this is not the case. Using aggregate U.S. data they estimate the parameters for a CES production function where capital, skilled and unskilled labor are embedded. They find that capital is a gross complement with skilled labor and a gross substitute for unskilled labor. Therefore, secular growth is skill-biased and is able to reproduce the rise in the skill premium observed in the U.S. since the start of the 1980s, highlighting the importance of worker training for productivity and inequality. Both Karabarbounis and Neiman (2014) and Eden and Gaggl (2018) depart from similar hypotheses in building their frameworks.

3 Model

Our model is of the Bewley-Aiyagari-Hugget variety:[3] An incomplete markets economy with overlapping generations of heterogeneous agents and partially uninsurable idiosyncratic risk that generates both an income and a wealth distribution. Households derive utility from non-durable consumption and leisure. Prior to entering the labor market, households choose their occupation type based on an idiosyncratic cost of acquiring

[1] Source: http://ethw.org/Early_Popular_Computers,_1950_-_1970.

[2] Not to mention holding a much larger quantity of information: in 1956, IBM's 305 RAMAC disk could hold 5 MB of information, while the computer on which this paper was written has a total of 4.78 TB in hard drive memory.

[3] See Bewley (2000), Aiyagari (1994), and Hugget (1993).

the necessary skills to perform its. For tractability, we assume that this decision is irreversible and mutually exclusive, and determines from which labor market the household will draw its wage over his lifetime. Cortes et al. (2020) show evidence that the main driver of decline in routine employment has been a reduction in inflow rates rather than increases in outflows. This is consistent with our assumption of inability of changing occupation type in the middle of working life, in spite of changing wage premia in other occupation types. After labor market entry, households then face an idiosyncratic stream of earnings in the form of wages, and make joint decisions about consumption, savings and hours worked.

For the production side of the economy, we draw heavily on the modeling strategy of Krusell et al. (2000) and Karabarbounis and Neiman (2014). There are three final goods sectors in the economy: Consumption goods, structure capital goods, and an equipment capital goods sector. This formulation allows us to express the price of equipment goods as a function of the level of technology in that sector relative to the consumption goods sector, which is viewed as a form of investment-specific technological change. The production function is extended with respect to the literature in order to encompass a total of four labor varieties: Non-routine cognitive, non-routine manual, routine cognitive, and routine manual. The asset structure used follows the same framework of Krusell et al. (2010) such that the change in investment prices affects the household saving decision. The centerpiece of the model is the production function, which uses inputs from the different occupation and capital types in order to produce final goods. Technological progress, in the form of total factor productivity growth, occupation-biased technological change, and investment-specific technological change, affects capital and labor demand and, thereby, occupation wage premia. The key mechanism driving wage dispersion in this economy can then be described as follows: As equipment prices fall, firms substitute away from routine manual labor to equipment capital and other types of labor which are more complementary with capital. Shifting demand of labor varieties coupled with limited labor mobility produces changes in wage premia over time, which may explain changes in wage dispersion across time.

In this section, we describe the resources and choices that households face, the production side of the economy, and the equilibrium concept. In the following section, we estimate the production function described in this section, in the spirit of Krusell et al. (2000), in order to use those estimates to calibrate the theoretical model to the U.S. economy in 1980.

3.1 Demographics

We assume the economy is populated by a set of $J-1$ overlapping generations, as in Brinca et al. (2016). We define a period in the model to correspond to one year. Thus, j, the household's age, varies between 0 (for age 20 households) and 80 (for age 100 households). Prior to joining the labor market, agents must make an irreversible and mutually exclusive occupation choice, deciding which labor market will determine their wages over the course of their lives. Households draw idiosyncratic utility from acquiring the necessary skills to join a given occupation type, κ_{io}, where $o \in O = \{\text{NRC}, \text{NRM}, \text{RC}, \text{RM}\}$ and i indexes the household. The idiosyncratic utility can be viewed as the personal cost (or benefit, if positive) of the process of acquiring skills to perform the tasks associated with a given occupation type, such as the effort (or joy) from studying in the case of cognitive occupations, for example. κ_{io} follows a type 1 extreme value distribution, H_o, with location parameter $\mu_{\kappa,o}$ and scale parameter $\sigma_{\kappa,o}$ in the tradition of discrete choice modeling of McFadden (1973).[4] Households choose the occupation where total utility is highest:

$$\tilde{V}_{io} = \kappa_{io} + V_o, \tag{1}$$

[4]Concretely, this formulation is the same as that used for unordered multinomial models where discrete choices are modeled as outcomes from an additive random utility model. See Cameron and Trivedi (2005) for a detailed exposition.

where V_o is expected utility from choosing occupation type o, κ_{io} is the idiosyncratic utility draw for occupation o. Assuming $\sigma_{\kappa,o} = 1$, $\forall o \in O$, this formulation allows us to write the probability of choosing an occupation o before κ_{io} is known:

$$p_o = \frac{e^{\mu_o + V_o}}{\sum_{l \in O} e^{\mu_l + V_l}}. \tag{2}$$

Equation 2 is also a closed form expression for the employment shares in our model.[5] Other than occupation, households differ in the value of their persistent idiosyncratic productivity shock, u_{ij}, permanent ability, a_i, and asset holdings, h_{ij}. Working age agents have to choose how much to work, n_{ij}, how much to consume, c_{ij}, and how much to save, h_{ij+1}, to maximize utility.

After retiring at age 65, households face an age-dependent probability of dying, $\pi(j)$, dying with certainty at age 100. $\omega(j) = 1 - \pi(j)$ defines the age-dependent probability of surviving, and so, at any given period, using a law of large numbers, the mass of retired agents of age $j \geq 45$ is equal to $\Omega_j = \prod_{t=45}^{t=j} \omega(t)$. A fraction of households leave unintended bequests which are redistributed in a lump-sum manner between the households that are currently alive, denoted by Γ. We include a bequest motive in this framework to make sure that the age distribution of wealth is empirically plausible, as in Brinca et al. (2019). Retired households make consumption and saving decisions and receive a retirement benefit, $\Psi(a_i)$. For simplicity, we assume that the public retirement benefit is constant until the agent's death and is equal to a fraction, ψ_{ss}, of the average earnings of an agent with permanent ability a_i at age $j = 44$ working 1/3 of his time. ψ_{ss} is such that the Social Security system breaks even in equilibrium.

[5]In order to find V_o for each occupation, we calibrate and solve a version of the model where occupations are randomly assigned in such a way that we match the employment weights of each occupation type in 1980. Employment shares used are computed from CPS data and are: $p_{\text{NRC}} = 0.302$, $p_{\text{NRM}} = 0.109$ $p_{\text{RC}} = 0.243$. We then compute the expected utility for each occupation type, V_o, at age 20 which we use to solve and calibrate the version with occupational choice.

3.2 Labor income

Labor productivity depends on three distinct elements which determine the amount of efficiency units each household is endowed with in each period: Age, j, permanent ability, a_i, and the idiosyncratic productivity shock, u_{ij}, which we assume follows an AR(1) process:

$$u_{ij} = \rho_u u_{ij-1} + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2). \tag{3}$$

Thus, household i's wage at age j is given by:

$$w_i(j, s_i, a_i, u_{it}) = w_o e^{\gamma_0 + \gamma_1 j + \gamma_2 j^2 + \gamma_3 j^3 + a_i + u_{ij}}, \tag{4}$$

where γ_1, γ_2 and γ_3 are estimated directly from the data to capture the age profile of wages, and γ_0 is set such that the age polynomial is equal to zero at age 20 in the model. Households' labor income also depends on the wage per efficiency unit of labor w_o, $o \in O \equiv \{\text{NRC}, \text{NRM}, \text{RC}, \text{RM}\}$, where o is the labor variety supplied by the household. Permanent ability is assigned at labor market entry and has variance $\sigma_{a,o}$ which depends on the occupation, in order to match within group wage dispersion. Appendix D describes how this is implemented in the algorithm.

3.3 Preferences

Household utility is given by $U(c_{ij}, n_{ij})$. It is increasing in consumption and decreasing in work hours, $n_{it} \in (0, 1]$, and is defined as:[6]

$$U(c_{it}, n_{it}) = \frac{c_{ij}^{1-\lambda}}{1-\lambda} - \chi \frac{n_{ij}^{1+\eta}}{1+\eta}, \tag{5}$$

where λ is the constant relative risk aversion coefficient and η is the inverse of the Frisch elasticity of labor supply. The utility function of retired households has one extra term,

[6] We assume that labor disutility depends only on the level of supply, not on occupation type.

as they gain utility from the bequest they leave to living generations:

$$D(h_{ij+1}) = \varphi \log(h_{ij+1}). \tag{6}$$

3.4 Technology

In this economy, three competitive final goods sectors exist: consumption, structure investment goods, and equipment investment goods. These are produced by transforming a single intermediate input using a linear production technology. All payments are made in the consumption good, which is the numeraire.

The consumption good is obtained by transforming a quantity $Z_{c,t}$ of intermediate input into output, which is then sold at price $p_{c,t}$ to both households and the government. The transformation technology is:

$$C_t + G_t = Z_{c,t}, \tag{7}$$

where $Z_{c,t}$ is the quantity of input, purchased at $p_{z,t}$ from a representative intermediate goods firm. Given that the consumption good is competitively produced, its price equals the marginal cost of production:

$$p_{c,t} = 1 = p_{z,t}. \tag{8}$$

Likewise, structure investment good firms produce output with a similar technology:

$$X_{s,t} = Z_{s,t}, \tag{9}$$

and therefore we have that $p_{s,t} = 1$. The production of $X_{e,t}$, the equipment investment good, uses the transformation technology:

$$X_{e,t} = \frac{Z_{e,t}}{\xi_t}, \tag{10}$$

where $Z_{e,t}$ is the quantity of input z used in the production of the final equipment good. $1/\xi_t$ is the level of technology used in the production of $X_{e,t}$ relative to the final consumption good. As ξ_t declines, the relative productivity in assembling the equipment good increases. We assume that ξ_t evolves exogenously in this economy. We obtain the price of the equipment good from the zero profit condition:

$$p_{e,t} = \xi_t p_{z,t} = \xi_t, \tag{11}$$

where $\xi_t = p_{e,t}/p_{c,t}$ is interpreted as the relative price of the equipment good.

A representative intermediate goods firm produces $Z_{c,t} + Z_{s,t} + Z_{e,t}$ using a constant returns to scale technology in capital and labor inputs, $y_t = F(K_{s,t}, K_{e,t}, N_{NRC,t}, N_{NRM,t}, N_{RCt}, N_{RM,t})$, where $K_{s,t}$ is structure capital and $K_{e,t}$ is capital equipment. The firm rents non-equipment capital at rate $r_{s,t}$, equipment at r_t^e and each labor variety at $w_{o,t}$, $o \in O$. Aggregate demand measured in terms of the consumption good, $Y_t = C_t + G_t + X_{s,t} + \xi_t X_{e,t}$, factor prices and the price of the intermediate good $p_{z,t}$ are taken as given. The firm chooses capital and labor inputs each period in order to maximize profits:

$$\Pi_{z,t} = p_{z,t} y_t - r_{s,t} K_{s,t} - r_{e,t} K_{et} - \sum_{o \in O} w_{ot} N_{ot}, \tag{12}$$

subject to:

$$y_t = Z_{c,t} + Z_{s,t} + Z_{e,t} = C_t + G_t + X_{s,t} + \xi_t X_{e,t} = Y_t. \tag{13}$$

This setup implies that $Z_{c,t} = C_t + G_t$, $Z_{s,t} = X_{s,t}$, $Z_{e,t} = \xi_t X_{e,t}$, and $F(.) = Y_t = C_t + G_t + X_{s,t} + \xi_t X_{e,t}$. We assume that the production function of intermediate goods is

Cobb-Douglas over non-equipment capital and CES over the remaining inputs:[7]

$$F(.) = A_t G(.) = A_t K_{s,t}^{\alpha} \left[\sum_{i=1}^{3} \varphi_i Z_{i,t}^{\frac{\sigma-1}{\sigma}} + \left(1 - \sum_{i=1}^{3} \varphi_i\right) N_{RM,t}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma(1-\alpha)}{\sigma-1}}, \tag{14}$$

$$Z_{1,t} = \left[\phi_1 K_{e,t}^{\frac{\rho_1-1}{\rho_1}} + (1-\phi_1) N_{\mathrm{NRC},t}^{\frac{\rho_1-1}{\rho_1}} \right]^{\frac{\rho_1}{\rho_1-1}}, \; Z_{2,t} = \left[\phi_2 K_{e,t}^{\frac{\rho_2-1}{\rho_2}} + (1-\phi_2) N_{\mathrm{NRM},t}^{\frac{\rho_2-1}{\rho_2}} \right]^{\frac{\rho_2}{\rho_2-1}},$$

$$Z_{3,t} = \left[\phi_3 K_{e,t}^{\frac{\rho_3-1}{\rho_3}} + (1-\phi_3) N_{\mathrm{RC},t}^{\frac{\rho_3-1}{\rho_3}} \right]^{\frac{\rho_3}{\rho_3-1}},$$

where A_t is total factor productivity, ϕ_i and φ_i are distribution parameters where $i = 1, 2, 3$, indicating the occupation types NRC, NRM, and RC. ρ_i is the elasticity of substitution between capital and the nested labor variety i, and σ is the elasticity of substitution between each composite $Z_{i,t}$ and routine manual labor. Complementarity between the two inputs in $Z_{i,t}$ requires that $\rho_i < \sigma$, as explained in Krusell et al. (2000).

Each variety of labor input is measured in efficiency units, $N_{o,t} \equiv h_{o,t} \varrho_{o,t}$, where $h_{o,t}$ is the quantity of hours worked in the aggregate and $\varrho_{o,t}$ is an efficiency index representing the latent quality per hour worked of labor of type o in period t. $\varrho_{o,t}$ can be interpreted as a occupation-specific technology level, due to research and development, or as human capital accumulation.

[7]Krusell et al. (2000), Karabarbounis and Neiman (2014), and Eden and Gaggl (2018) use CES production functions where capital equipment is nested with all labor varieties except for RM, which is isolated. The reason for this setup is the set of symmetry restrictions on substitution elasticities imposed by the CES functional form, as explained in Krusell et al. (2000). In a nutshell, this nesting form allows for complementarity between capital and differentiated labor (NRC NRM, RC) while permitting the elasticities of substitution between routine routine manual labor and other labor varieties to be different. Our version is an extension of this framework with a finer breakdown over labor varieties. In estimating the production function, we use the Simulated pseudo-Maximum Likelihood Estimation (SPMLE) method proposed by Ohanian et al. (1997) which was also applied in Krusell et al. (2000). Our application is described in the next section.

Firm maximization implies that marginal products equal factor prices:[8]

$$w_{\mathrm{NRC},t} = \Xi_t \varphi_1 \left[\phi_1 \left(\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right)^{\frac{\rho_1 - 1}{\rho_1}} + (1-\phi_1) \right]^{\frac{\sigma-\rho_1}{(\rho_1-1)\sigma}} [1-\phi_1] \varrho_{\mathrm{NRC},t}, \tag{15}$$

$$w_{\mathrm{NRM},t} = \Xi_t \varphi_2 \left[\phi_2 \left(\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right)^{\frac{\rho_2 - 1}{\rho_2}} + (1-\phi_2) \left(\frac{N_{\mathrm{NRM},t}}{N_{\mathrm{NRC},t}} \right)^{\frac{\rho_2 - 1}{\rho_2}} \right]^{\frac{\sigma-\rho_2}{(\rho_2-1)\sigma}}$$
$$[1-\phi_2] \left(\frac{N_{\mathrm{NRM},t}}{N_{\mathrm{NRC},t}} \right)^{-\frac{1}{\rho_2}} \varrho_{\mathrm{NRM},t}, \tag{16}$$

$$w_{\mathrm{RC},t} = \Xi_t \varphi_3 \left[\phi_3 \left(\frac{K_{s,t}}{N_{\mathrm{NRC},t}} \right)^{\frac{\rho_3 - 1}{\rho_3}} + (1-\phi_3) \left(\frac{N_{\mathrm{RC},t}}{N_{\mathrm{NRC},t}} \right)^{\frac{\rho_3 - 1}{\rho_3}} \right]^{\frac{\sigma-\rho_3}{(\rho_3-1)\sigma}}$$
$$[1-\phi_3] \left(\frac{N_{\mathrm{RC},t}}{N_{\mathrm{NRC},t}} \right)^{-\frac{1}{\rho_3}} \varrho_{\mathrm{RC},t}, \tag{17}$$

$$w_{\mathrm{RM},t} = \Xi_t (1 - \varphi_1 - \varphi_2 - \varphi_3) \left(\frac{N_{\mathrm{RM},t}}{N_{\mathrm{NRC},t}} \right)^{-\frac{1}{\sigma}} \varrho_{\mathrm{RM},t}, \tag{18}$$

$$r_{s,t} = A_t \alpha \left[\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right]^{\alpha - 1} \Lambda_t^{\frac{\sigma(1-\alpha)}{\sigma-1}}, \tag{19}$$

$$r_{e,t} = \Xi_t \Bigg[\varphi_1 \left(\phi_1 \left[\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right]^{\frac{\rho_1-1}{\rho_1}} + [1-\phi_1] \right)^{\frac{\sigma-\rho_1}{(\rho_1-1)\sigma}} \phi_1 \left(\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right)^{-\frac{1}{\rho_1}} +$$
$$\varphi_2 \left(\phi_2 \left[\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right]^{\frac{\rho_2-1}{\rho_2}} + [1-\phi_2] \left[\frac{N_{\mathrm{NRM},t}}{N_{\mathrm{NRC},t}} \right]^{\frac{\rho_2-1}{\rho_2}} \right)^{\frac{\sigma-\rho_2}{(\rho_2-1)\sigma}} \phi_2 \left(\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right)^{-\frac{1}{\rho_2}} +$$
$$\varphi_3 \left(\phi_3 \left[\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right]^{\frac{\rho_3-1}{\rho_3}} + [1-\phi_3] \left[\frac{N_{\mathrm{RC},t}}{N_{\mathrm{NRC},t}} \right]^{\frac{\rho_3-1}{\rho_3}} \right)^{\frac{\sigma-\rho_3}{(\rho_3-1)\sigma}} \phi_3 \left(\frac{K_{e,t}}{N_{\mathrm{NRC},t}} \right)^{-\frac{1}{\rho_3}} \Bigg], \tag{20}$$

[8]Marginal products are expressed as functions of the ratios between each factor and the non-routine cognitive labor for the purpose of constructing the solution algorithm.

where[9]

$$\Xi_t = A_t \left[\frac{K_{s,t}}{N_{\text{NRC},t}}\right]^{\alpha} [1-\alpha]\Lambda_t^{\frac{1-\sigma\alpha}{\sigma-1}}.$$

The capital laws of motion are:

$$K_{s,t+1} = (1-\delta_s)K_{s,t} + X_{s,t}, \tag{21}$$

$$K_{e,t+1} = (1-\delta_e)K_{e,t} + X_{e,t}, \tag{22}$$

where δ_s and δ_e are the depreciation rates.

3.5 Government

The social security system is managed by the government and runs a balanced budget. Revenues are collected from taxes on employees and on the representative firm at rates τ_{ss} and $\tilde{\tau}_{ss}$, respectively, and are used to pay retirement benefits, Ψ.

The government taxes consumption, τ_c, and capital income, τ_k, at flat rates. The labor income tax follows a non-linear functional form as in Heathcote et al. (2019) and Benabou (2002):

$$y_a = 1 - \theta_0 y^{-\theta_1}, \tag{23}$$

where θ_0 and θ_1 define the level and progressivity of the tax schedule, respectively. y is the pre-tax labor income and y_a is the after-tax labor income.[10]

9Variable Λ_t is defined as:

$$\Lambda_t = \varphi_1 \left(\phi_1 \left[\frac{K_{e,t}}{N_{\text{NRC},t}}\right]^{\frac{\rho_1-1}{\rho_1}} + [1-\phi_1]\right)^{\frac{\rho_1(\sigma-1)}{(\rho_1-1)\sigma}} + \varphi_2 \left(\phi_2 \left[\frac{K_{e,t}}{N_{\text{NRC},t}}\right]^{\frac{\rho_2-1}{\rho_2}} + [1-\phi_2]\left[\frac{N_{\text{NRM},t}}{N_{\text{NRC},t}}\right]^{\frac{\rho_2-1}{\rho_2}}\right)^{\frac{\rho_2(\sigma-1)}{(\rho_2-1)\sigma}}$$
$$+ \varphi_3 \left(\phi_3 \left[\frac{K_{e,t}}{N_{\text{NRC},t}}\right]^{\frac{\rho_3-1}{\rho_3}} + [1-\phi_3]\left[\frac{N_{\text{RC},t}}{N_{\text{NRC},t}}\right]^{\frac{\rho_3-1}{\rho_3}}\right)^{\frac{\rho_3(\sigma-1)}{(\rho_3-1)\sigma}} + (1-\varphi_1-\varphi_2-\varphi_3)\left(\frac{N_{\text{RM},t}}{N_{\text{NRC},t}}\right)^{\frac{\sigma-1}{\sigma}}.$$

10See the Holter et al. (2014) for a detailed discussion of the properties of this tax function.

Tax revenues from consumption, labor and capital income taxes are used to finance public consumption of goods, G_t, public debt interest expenses, $r_t B_t$, and lump sum transfers, g_t, which are a residual which clears the government budget constraint. Denoting social security revenues by R_t^{ss} and the other tax revenues as T_t, the government budget constraint is defined as:

$$T_t = G_t + r_t B_t + g_t, \tag{24}$$

$$\Psi_t \left(\sum_{j \geq 45} \Omega_j \right) = R_t^{ss}. \tag{25}$$

3.6 Asset Structure

Households hold three asset types: Structures capital, $k_{s,ij}$, equipment capital, $k_{e,ij}$, and government bonds, b_{ij}. There is no investment-specific technological change in the steady state, i.e., $\xi_{t+1} = \xi_t = \xi$, so we drop the time index on return rates for this exposition. The return rate on the government bond must satisfy:

$$\frac{1}{\xi} \left[\xi + (r_e - \xi \delta_e)(1 - \tau_k) \right] = 1 + r(1 - \tau_k), \tag{26}$$

which follows from non-arbitrage: investing in equipment capital must yield the same return as investing the same amount in bonds. By the same token, the return rate on structure capital must satisfy:

$$\frac{1}{\xi} \left[\xi + (r_e - \xi \delta_e)(1 - \tau_k) \right] = 1 + (r_s - \delta_s)(1 - \tau_k). \tag{27}$$

Total assets for the consumer are defined as:

$$h_{ij} \equiv \xi k_{e,ij} + b_{ij} + k_{s,ij}, \tag{28}$$

3.7 Household Problem

On any given period a household is defined by age, j, asset position h_{ij}, permanent ability a_i, a persistent idiosyncratic productivity shock u_{ij}. A working-age household chooses consumption, c_{ij}, work hours, n_{ij}, and future asset holdings, h_{ij+1}, to solve his optimization problem. The household budget constraint is given by:

$$c_{ij}(1+\tau_c)+\xi k_{e,ij+1}+b_{ij+1}+k_{s,ij+1}=[\xi+(r_e-\xi\delta_e)(1-\tau_k)]\,k_{e,ij}+[1+r(1-\tau_k)]b_{ij}+ \\ [1+(r_s-\delta_s)(1-\tau_k)]k_{s,ij}+q\Gamma+Y^N+g, \tag{29}$$

where Y^N is the household's labor income after social security and labor income taxes, and $q=1/(1+r(1-\tau_k))$. Using 26 and 27, in equilibrium we can rewrite the budget constraint as:

$$c_{ij}(1+\tau_c)+h_{ij+1}=(h_{ij}+\Gamma)[1+r(1-\tau_k)]+Y^N+g. \tag{30}$$

The household problem can then be formulated recursively as:

$$V(j,h_{ij},o_i,a_i,u_{ijt})=\max_{c_{ij},n_{ij},h_{ij+1}}\left[U\left(c_{ij},n_{ij}\right)+\beta\mathbb{E}_{u_{j+1}}\left[V(j+1,h_{it+1},o_i,a_i,u_{ij+1})\right]\right]$$

s.t.:

$$c_{ij}(1+\tau_c)+h_{ij+1}=(h_{ij}+\Gamma)[1+r(1-\tau_k)]+Y^N+g$$

$$Y^N=\frac{n_{ij}w\left(j,o_i,a_i,u_{ij}\right)}{1+\tilde{\tau}_{ss}}\left(1-\tau_{ss}-\tau_l\left[\frac{n_{ij}w\left(j,o_i,a_i,u_{ij}\right)}{1+\tilde{\tau}_{ss}}\right]\right)$$

$$n_{ij}\in(0,1],\quad h_{ij}\geq 0,\quad h_{i0}=0\ \forall i,\quad c_{ij}>0.$$

The problem of a retired household differs in three features: The age dependent probability of dying $\pi(j)$, the bequest motive $D(h_{ij+1})$, and labor income, which is replaced by constant retirement benefit depending on permanent ability, $\Phi(a_i)$. Therefore, the retired household's problem is defined as:

$$V(j, h_{ij}, a_i) = \max_{c_{ij}, h_{i,j+1}} \left[U\left(c_{ij}, h_{ij+1}\right) + \beta(1-\pi(j))V(j+1, h_{ij+1}, a_i) + \pi(j)D(h_{ij+1}) \right]$$

s.t.:

$$c_{ij}(1+\tau_c) + h_{ij+1} = (h_{ij} + \Gamma)[1 + r(1-\tau_k)] + \Psi(a_i) + g$$

$$h_{ij+1} \geq 0, \quad c_{ij} > 0.$$

3.8 Stationary Recursive Competitive Equilibrium

$\Phi(j, h_{ij}, s_i, a_i, u_{ij})$ is the measure of agents with corresponding characteristics $(j, h_{ij}, s_i, a_i, u_{ij})$. The stationary recursive competitive equilibrium is defined by:[11]

1. Taking factor prices and initial conditions as given, the value function $V(j, h_{ij}, s_i, a_i, u_{ij})$ and the policy functions, $s_{i0}(\kappa_{io})$, $c_{ij}(h_{ij}, s_i, a_i, u_{ij})$, $h_{ij+1}(h_{ij}, s_i, a_i, u_{ij})$, and $n_{ij}(h_{ij}, s_i, a_i, u_{ij})$, solve the household's optimization problem.

2. Markets clear:

$$\xi K_e + B + K_s = \int h + \Gamma \, d\Phi,$$

$$N_{\text{RM}} = \varrho_{\text{RM}} \int n_{\text{RM}} \, d\Phi, \quad N_{\text{RC}} = \varrho_{\text{RC}} \int n_{\text{RC}} \, d\Phi,$$

$$N_{\text{NRM}} = \varrho_{\text{NRM}} \int n_{\text{NRM}} \, d\Phi, \quad N_{\text{NRC}} = \varrho_{\text{RM}} \int n_{\text{NRC}} \, d\Phi,$$

$$C + G + \delta_s K_s + \xi \delta_e K_e = F(K_s, K_e, N_{\text{NRC}}, N_{\text{NRM}}, N_{\text{RC}}, N_{\text{RM}}).$$

3. Equations 16-20 hold.

4. The government budget balances:

$$G + rB + g = \int \tau_k r(h + \Gamma) + \tau_c c + n\tau_l \left[\frac{nw(j, o, a, u)}{1 + \tilde{\tau}_{ss}} \right] d\Phi.$$

[11]The time index is dropped from aggregate variables, given that this is characterization of the steady state.

5. The social security system balances:

$$\int_{j \geq 45} \Psi \, d\Phi = \frac{\tilde{\tau}_{ss} + \tau_{ss}}{1 + \tilde{\tau}_{ss}} \left(\int_{j<45} nw \, d\Phi \right).$$

6. The assets of the deceased at the beginning of the period are uniformly distributed among the living:

$$\Gamma \int \omega(j) d\Phi = \int (1 - \omega(j)) \, h \, d\Phi.$$

4 Production function estimation

In this section, we describe the stochastic specification of the production function model, the equations to be estimated, and the results. The estimation strategy is as in Krusell et al. (2000). Parameter estimates from this section are used to produce a baseline calibration of the theoretical model, with which to run experiments of the impact of technological change on wage and earnings dispersion. The data used in the estimation is described in Appendix B.

4.1 Stochastic specification

The stochastic elements in our model are the unobserved technology components: (i) the relative technological level of the investment good sector; (ii) the set of labor-specific efficiency indices; and (iii) the factor-neutral technological process. We assume that the relative price of equipment ($\tilde{\xi}_t = \xi_t / \xi_{t-1}$) is trend stationary, and confirm this with a Dickey-Fuller test. We assume that the labor efficiency index processes have different linear trend for each labor variety. Defining the processes in logs we have:

$$\psi_t \equiv \ln(\varrho_t), \quad \psi_t = \psi_0 + \psi_1 t + \nu_t, \tag{31}$$

where ψ_t is a (4×1) vector of the log of the latent efficiency indices, ψ_0 is a (4×1) vector of constants which specify the value of the indices at the beginning of the sample, ψ_1 is a (4×1) vector of growth rates, and ν_t is a (4×1) vector of shock processes that we assume to be multivariate normal, i.i.d. with covariance matrix Ω: $\nu_t \sim N(0, \Omega)$. The i.i.d. assumption simplifies the identification of the factor-neutral technological change, A_t, which is described below.

4.2 Equation specification

We use a system with two sets of equations obtained from the first order conditions of agents in order to estimate the model: (i) the wage bills relative to the routine manual labor variety; and (ii) a no-arbitrage condition between investing in equipment and non-equipment capital. These are defined as follows:

$$\frac{w_{o,t} h_{o,t}}{w_{\text{RM},t} h_{\text{RM},t}} = wbr_{o,t}(\psi_t, X_t; \theta), \qquad s \in o = \{\text{NRC}, \text{NRM}, \text{RC}\}, \tag{32}$$

and

$$1 + [F_{K_s}(\psi_{t+1}, X_{t+1}; \theta) - \delta_{s,t+1}] = E_t \left(\frac{\xi_{t+1}}{\xi_t} \right) (1 - \delta_{et+1}) + \frac{F_{K_e}(\psi_{t+1}, X_{t+1}; \theta)}{\xi_t} \tag{33}$$

where 33 is obtained from equation 27, assuming that $\xi_t \neq \xi_{t+1}$, and where we substituted the return rates by factor marginal productivities. Depreciation rates are indexed by t since they change over the time (see Appendix B). $wbr_{o,t}$ are functions of X_t and θ. X_t is the vector of inputs, and depreciation rates $\{K_{s,t}, K_{e,t}, h_{\text{NRC},t}, h_{\text{NRM},t}, h_{\text{RC},t}, h_{\text{RM},t}, \delta_{s,t}, \delta_{e,t}\}$. The vector θ is the set of parameters $\{\alpha, \rho_1, \rho_2, \rho_3, \phi_1, \phi_2, \phi_3, \varphi_1, \varphi_2, \varphi_3, \psi_0, \psi_1, \Omega, \eta_\omega, K_{e,0}\}$, which includes the first observation of the equipment capital stock, which we estimate and use to build the capital stock series for subsequent periods in the estimation. η_ω is the standard deviation of the error term in the equipment price equation, which we specify below. Like Krusell et al. (2000), we assume that there is no risk premium in equation 33, and that tax treatment is identical between equipment and non-equipment capital returns. Finally, we substitute the first term on the right hand side of equation 33 with $E_t\left(\xi_{t+1}/\xi_t\right)\left(1-\delta_{et}[1-\tau_{kt}]\right)+\omega_t$, where ω_t is the i.i.d. forecast error and $\omega_t \sim N\left(0,\eta_\omega^2\right)$. This set of assumptions imply that $A_t = Y_t/G(.)$ from equation 14.

Data for the labor inputs in hours and the hourly (nominal) wages are used to obtain the left side of the set of equations 32. We use a measure of GDP at constant prices to find A_t. The construction of the structure capital stock, depreciation rates, and relative prices is discussed on Appendix B. Given that this is a non-linear system of eight equations with unobserved state variables, standard linear Kalman filter techniques cannot be applied to estimate the parameter vector θ. Ohanian et al. (1997) propose a two-step version of the SPML estimator to find θ for this type of problem, which we detail on Appendix C.

The parameter vector θ has a dimension of 36. Our sample contains 49 observations for each equation. We reduce the number of parameters to estimate by external calibration or by setting *a priori* restrictions. First, we impose that Ω be a diagonal matrix and that the variance of the disturbances be identical for all labor types. Thus, $\Omega = \eta_v^2 I_4$, where η_v^2 is the common innovation variance and I_4 is a (4×4) identity matrix. Second, we fix ψ_{40}, the initial level of the latent efficiency index of routine manual workers, which is not identified. Third, we set the income share of structures to 0.04. Finally, we regress the variation rate of the relative price of equipment on a linear trend. We set η_ω to be equal to the estimated standard deviation of the error term in the regression $\tilde{\sigma}_\omega = 0.032$. This reduces the number of parameters to be estimated to 19: The common variance of the latent processes, η_v^2, the elasticities, $\sigma, \rho_1, \rho_2, \rho_3$, the production function share parameters, $\phi_1, \phi_2, \phi_3, \varphi_1, \varphi_2, \varphi_3$, the parameters governing the latent state variables, except for $\psi_{4,0}$, and the initial level of capital equipment, $K_{e,0}$.

4.3 Results

The model is estimated using data from 1967 to 2016 and the Simulated Pseudo Maximum Likelihood Estimation (SPMLE) procedure. Table 1 shows estimated elasticities for each of the occupation types.

Elasticity estimates for the nested occupation types are all consistent with capital-occupation complementarity, i.e., $\sigma > \rho_i$, $i = 1, 2, 3$. The estimation of these elasticities is one of the contributions of this paper to the literature. The most comparable estimates are provided by Eden and Gaggl (2018), who specify a CES production function with non-routine labor nested with capital. In contrast to our estimates of 0.5 and 2.1 for NRC and NRM labor, respectively, they estimate an elasticity of substitution of 1.4 for non-routine labor. For routine manual labor, their estimate is 8.0 for routine occupations, compared to our elasticity of 5.6 for RM. Although less comparable, Krusell et al. (2000) obtain a value of 0.67 for skilled labor, and 1.67 for unskilled labor. As to the processes of occupation-specific technology, we estimate that only the non-routine cognitive occupations have experienced positive growth, while routine manual labor has suffered the largest decline. We know of no other comparable estimates in the literature.

Figure 3 shows the model fit to target moments over time. Figure 3a shows the aggregate *ex post* return rates of equipment and structures implied by our model, which are zero in expectation as per our assumption. They have a 4% average, as in Krusell et al. (2000), although a slightly increasing trend from the early 2000s onward.

Figure 3b plots the wage bill ratios implied by the model, as specified by the set of equations (32), and the data. Model predictions closely track the data. The NRC wage bill shoots up from close to on par with RM labor in 1968 to 3.5 in 2015. In contrast, NRM and RC wage bills grow slowly upwards relative to that of RM occupations, which is explained by both their lower level of complementarity with equipment capital as well as their declining level of productivity.

Figure 3c shows the model fit to the wage premia of each occupation relative to RM.

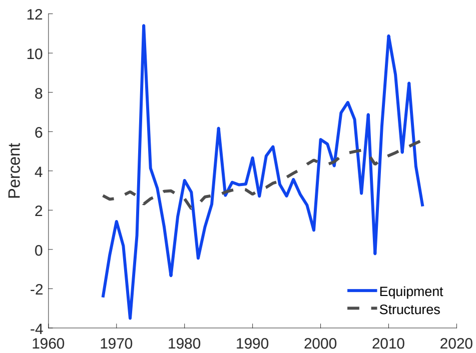
Table 1: Elasticity estimates

Parameter	Description	Value
σ	EOS RM	5.564
ρ_1	EOS NRC	0.497
ρ_2	EOS NRM	2.055
ρ_3	EOS RC	5.029
ϕ_1	Share NRC	0.378
ϕ_2	Share RM	0.086
ϕ_3	Share RM	0.279
φ_1	Share composite NRC	0.160
φ_2	Share composite NRM	0.045
φ_3	Share composite RC	0.023
$\psi_{0,1}$	Intercept NRC	0.859
$\psi_{0,2}$	Intercept NRM	1.936
$\psi_{0,3}$	Intercept RC	3.582
$\psi_{1,1}$	Slope NRC	0.002
$\psi_{1,2}$	Slope NRM	-0.006
$\psi_{1,3}$	Slope RC	-0.001
$\psi_{1,4}$	Slope RM	-0.010
$K_{e,0}$	Starting equipment capital	582

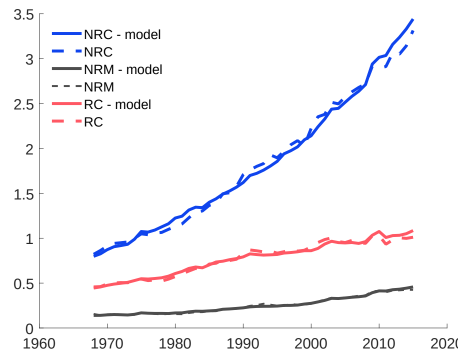
As in the previous figure, the dashed lines indicate the data and the solid lines the model predictions. In all cases, the model tracks the data closely. This is important given that our goal is to use the estimated parameters to calibrate the theoretical model, and the key force driving earnings dispersion is the change in wage premia across groups.

Finally, Figure 3d displays our estimate of total factor productivity in the U.S. for this period. From 1968 to 2008, TFP increased by almost 30% and then fell to around 20% in the following years. For comparison, the estimate of total factor productivity by the Penn World Table increases by 30% from 1968 to 2015 (FRED).

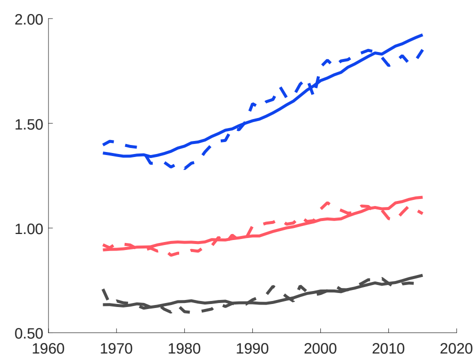
In conclusion, we provide new estimates for the elasticity of substitution between equipment capital and the set of occupations defined above. Our model is broadly compatible with the data, especially the occupation wage premia, which is crucial for ensuring that the predictions of the theoretical model are consistent with the data.



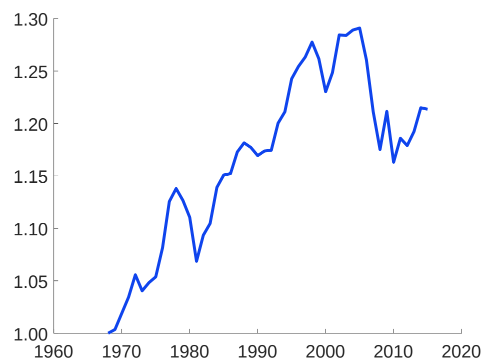
(a) Returns to capital



(b) Wage bill ratio by occupation



(c) Wage premia



(d) Total factor productivity

Note: The estimates presented cover the period from 1968 to 2015 as we lose both the first and the last period of the sample in order to estimate the model. In Figure 3d, total factor productivity is normalized to 1 in 1968. Construction of the measures is described in Appendix B.

Figure 3: Empirical model fit to target and non-target moments.

5 Calibration

This section describes the calibration of the baseline model to match the U.S. economy in 1980. Parameters are either set directly (i.e., without solving the full model) to match their empirical counterparts, or estimated by simulated method of moments (SMM). Table 2 lists parameter values and sources.

Table 2: External calibration summary

Description	Parameter	Value	Source
Preferences			
Inverse Frisch elasticity	η	3.000	Assumption
Risk aversion parameter	λ	1.000	Assumption
Labor productivity			
Parameter 1 age profile of wages	γ_1	0.265	Author's calculations
Parameter 2 age profile of wages	γ_2	-0.005	Author's calculations
Parameter 3 age profile of wages	γ_3	0.000	Author's calculations
Variance of idiosyncratic risk	σ_ϵ	0.307	Author's calculations
Persistence idiosyncratic risk	ρ_u	0.335	Author's calculations
Location of the cost of choosing NRC	μ_{NRC}	-5.616	Author's calculations
Location of the cost of choosing NRM	μ_{NRM}	3.613	Author's calculations
Location of the cost of choosing RC	μ_{RC}	0.194	Author's calculations
Location of the cost of choosing RM	μ_{RM}	0.000	Normalization
Technology			
Equipment depreciation rate	δ_e	0.106	Authors' calculations
Structures depreciation rate	δ_s	0.026	Authors' calculations
Share NRC	ϕ_1	0.378	Authors' calculations
Share NRM	ϕ_2	0.086	Authors' calculations
Share RC	ϕ_3	0.279	Authors' calculations
Share composite NRC	φ_1	0.160	Authors' calculations
Share composite NRM	φ_2	0.045	Authors' calculations
Share composite RC	φ_3	0.023	Authors' calculations
EOS NRC	ρ_1	0.497	Authors' calculations
EOS NRM	ρ_2	2.055	Authors' calculations
EOS RC	ρ_3	5.029	Authors' calculations
EOS RM	σ	5.564	Authors' calculations
Latent efficiency NRC	ϱ_1	2.734	Authors' calculations
Latent efficiency NRM	ϱ_2	4.955	Authors' calculations
Latent efficiency RC	ϱ_3	34.662	Authors' calculations
Latent efficiency RM	ϱ_4	0.378	Authors' calculations
Total factor productivity	A	16.728	Authors' calculations
Relative price of investment goods	ξ	1.000	Normalization
Government and SS			
Consumption tax rate	τ_c	0.054	Mendoza et al. (1994)
Capital income tax rate	τ_k	0.469	Mendoza et al. (1994)
Tax scale parameter	θ_0	0.850	Wu (2020)
Tax progressivity parameter	θ_1	0.187	Wu (2020)
Government expenditures to GDP	G/Y	0.065	FRED
Government debt to GDP	B/Y	0.320	FRED
SS tax employees	τ_{ss}	0.061	Social Security Bulletin, July 1981
SS tax employers	$\tilde{\tau}_{ss}$	0.061	Social Security Bulletin, July 1981

5.1 External calibration

Demographics We set the inverse of the Frisch elasticity of labor supply, η, to 3 which is a standard value in the literature. The risk aversion parameter, λ, is set to 1, i.e., logarithmic utility.

Labor productivity The wage profile through the life cycle (see equation 4) is calibrated directly from the data. We run the following regression, using Panel of Study of Income Dynamics (PSID) data:

$$\ln(w_{it}) = a + \gamma_1 j + \gamma_2 j^2 + \gamma_3 j^3 + \varepsilon_{it}. \tag{34}$$

where j is the age of individual i. We then use the residuals of the equation to estimate the parameters governing the idiosyncratic shock ρ and σ_ϵ. The scale parameters of the cost of choosing an occupation ($\mu_{\text{NRC}}, \mu_{\text{NRM}}, \mu_{\text{RC}}, \mu_{\text{RM}}$) are set such that they match the employment shares observed in 1980. This procedure is explained in Section 3. The location parameter, μ_{RM}, is normalized to 1.0.

Technology The equipment and structures depreciation rates are set to match those used in the estimation of the empirical model, and described in Appendix B. The production function is calibrated using the parameters estimated from the empirical model. The efficiency indices of each occupation are set to match those of of the empirical model in 1980. The level of total factor productivity is set to the estimate from the empirical model for 1980.

Government We set θ_0 and θ_1 to the estimates obtained by Wu (2021) for 1980. For the social security rates we assume no progressivity. Both social security tax rates, on behalf of the employer and on behalf of the employee, are set to 0.06, the average rate in 1980. Finally, we set τ_c and τ_k to match the values obtained in Mendoza et al. (1994) for 1980, i.e, $\tau_c = 0.05$, $\tau_k = 0.47$. Government debt to GDP is obtained from FRED.

Government expenditures to GDP are set to match the share of defense expenditures to GDP, obtained from FRED.

5.2 Internal calibration

To calibrate the parameters for which we do not have any direct empirical counterparts, $\{\beta, \chi, \varphi, \sigma_{NRC}, \sigma_{NRM}, \sigma_{RC}, \sigma_{RM}\}$, we use a simulated method of moments, for which we construct the following loss function:

$$L(\tilde{\theta}) = ||M_m - M_d||, \tag{35}$$

where $\tilde{\theta}$ is the vector of parameters to be estimated and M_m and M_d being the moments in the 1980 data and in the model respectively. Our estimate, $\tilde{\theta}^*$, is obtained by minimizing (35).

We use the ratio between average wealth of 65 and older to the average wealth in the economy as the target for the utility of bequests parameter. The discount factor is set by targeting the capital-to-output ratio. This measure is obtained from the estimation of the empirical model of section 4. Disutility from work targets hours worked, and we calibrate the occupation-specific variances of ability to target the variance of log earnings observed in the data for each occupation. Calibration fit is presented on Table 3. Table 4 presents the parameters calibrated internally.

Table 3: Calibration fit

Data moment	Description	Source	Model	Data
65-on/all	Average wealth of households 65 and over	US Census Bureau	1.310	1.311
K/Y	Capital to output	Author's calculations	1.412	1.412
$\overline{n}$	Fraction of hours worked	BEA	1/3	1/3
$\text{Var}\ln(w_{\text{NRC}})$	Variance of log wages (NRC)	CPS	0.300	0.294
$\text{Var}\ln(w_{\text{NRM}})$	Variance of log wages (NRM)	CPS	0.218	0.207
$\text{Var}\ln(w_{\text{RC}})$	Variance of log wages (RC)	CPS	0.260	0.253
$\text{Var}\ln(w_{\text{RM}})$	Variance of log wages (RM)	CPS	0.268	0.261

Table 4: Parameters calibrated internally

Parameter	Value	Description
φ	7.093	Bequest utility
β	0.968	Discount factor
χ	56.57	Disutility of work
$\sigma_{a,\text{NRC}}$	0.391	Variance of ability NRC
$\sigma_{a,\text{NRM}}$	0.381	Variance of ability NRM
$\sigma_{a,\text{RC}}$	0.304	Variance of ability RC
$\sigma_{a,\text{RM}}$	0.441	Variance of ability RM

6 Quantitative results

In this section, we use our model calibrated to the U.S. economy in 1980 in order to answer the two questions described in the beginning: To what extent does technological change explain the observed increase in earnings dispersion? How does technological change affect the optimal progressivity of the tax system?

6.1 Sources of earnings inequality variation

The main experiment conducted in this section is to recalibrate the model to match technological and tax changes in 2015. We then decompose the variation in the earnings inequality statistics between steady states to identify the role of investment-specific technological change, labor-specific technology and TFP on the increased earnings dispersion. We also compare the magnitude of that role to other possible sources of variation in earnings dispersion, such as taxation.

Parameters related to tastes, individual productivity processes and the production function are kept constant between steady states: The age profile of wages (γ_1, γ_2, γ_3), the idiosyncratic productivity process (ρ_u and σ_ϵ), preferences (λ, η, β), the ability variance parameters ($\sigma_{a,o}$, $o \in O$), and production function shares and elasticities. Parameters changed in order to make a prediction regarding the state of the economy in 2015 are listed on Table 5. The main shifts are in technology parameters, idiosyncratic occupation costs, and tax rates.

In the new steady state, we set the relative price of investment goods to be equal to 40% of the initial price index, which mimics the fall measured in the data between 1980 and 2015. The labor efficiency indices are set to their 2015 levels, using the functional forms of those processes estimated in section 4. Likewise, TFP is set to equal the estimated level in 2015. The location parameters of the idiosyncratic cost distributions are set such that they match the occupation employment shares observed in 2015.

The scale and the progressivity parameters of the labor income tax schedule are set to match the estimate of Wu (2021). Social Security tax rates are those described in Brinca et al. (2016) for the U.S. economy. Government debt to output is the 2014-2016 average of government debt to GDP provided by FRED. Both the consumption tax and the capital income tax are calculated using the method in Mendoza et al. (1994).

Table 5: Parameter changes

Parameter	Description	1980	New SS
τ_c	Consumption tax	0.054	0.050
τ_k	Capital income tax	0.469	0.360
B/Y	Government debt to output	0.320	1.020
τ_{ss}	Employee SS tax	0.061	0.077
$\tilde{\tau}_{ss}$	Employer SS tax	0.061	0.077
θ_0	Tax scale	0.850	0.922
θ_1	Tax progressivity	0.187	0.137
ξ	Investment price	1.000	0.405
ϱ_1	Latent efficiency NRC	2.734	2.986
ϱ_2	Latent efficiency NRM	4.955	4.051
ϱ_3	Latent efficiency RC	34.662	33.907
ϱ_4	Latent efficiency RM	0.378	0.267
μ_{NRC}	NRC cost location parameter	-5.616	-6.882
μ_{NRM}	NRM cost location parameter	3.613	2.994
μ_{RC}	RC cost location parameter	0.194	-2.027

Table 6 contains the fit of the model moments to the data in 1980 and 2015, all of which are non-targeted.

In the first section of the table, we compare relative input quantities from the theoretical model to those obtained from estimating the empirical model of the production function in section 4. Relative inputs quantities are fairly close to our estimates, with the exception of the growth of equipment capital, which the theoretical model substantially underestimates relative to the empirical model.

The second section shows the wage changes by occupation between both steady states. The model overestimates wage growth for all occupations, relative to the data. This is unsurprising, given that there are other forces at work in the U.S. economy that are not present in the model, such as increased participation of women in the workforce, for example. However, as can be seen in the next section of the table, wage premia levels and changes are very close to the data in both years, which is key in terms of accounting for the change in earnings dispersion.

The final two sections present measures of wage and earnings inequality. In 1980, the model predicts an overall level of wage dispersion which is slightly above its data counterpart. The variances of log wages per occupation in 1980 are very close to their data counterparts, given that the variances of ability in each occupation were calibrated by targeting this set of moments. From 1980 to 2015, the variance aggregate log wages increase 44% in the data, compared to only 23% in the model. The reason for this disparity is that we do not take into account any sources of changes in within-occupation wage dispersion. In fact, there is no change in the within-occupation wage variance predicted by the model between 1980 and 2015, as can be observed from the table.

We now turn to the change in aggregate earnings dispersion. Figure 4a shows the response of labor income dispersion measures to the set of parameter shifts presented on Table 5. The first bar indicates the change in the earnings Gini observed in the data between those periods, while the second bar indicates the change predicted by the model as a result of the baseline parameter shifts shown in Table 5. Figure 4a, in the top left panel, compares the change in the earnings Gini observed in the data between 1980 and 2015 to the prediction from the theoretical model. Our baseline experiment replicates

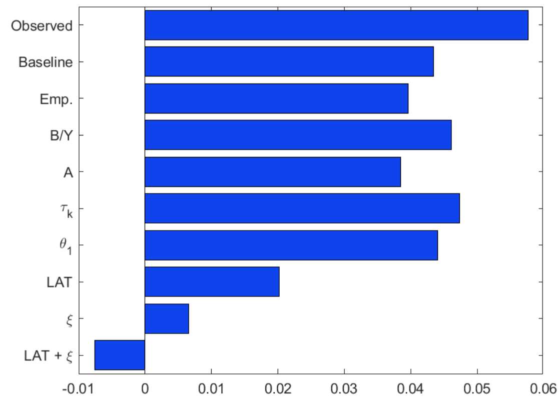
Table 6: Theoretical model fit

Variable	1980 Model	1980 Data	2015 Model	2015 Data
K_e/N_{NRC}	6.68	7.80	17.74	39.14
N_{NRM}/N_{NRC}	0.62	0.55	0.45	0.43
N_{RC}/N_{NRC}	10.09	9.10	5.49	5.66
N_{RM}/N_{NRC}	0.16	0.16	0.05	0.05
NRC wage	1.00	1.00	1.36	1.28
NRM wage	1.00	1.00	1.12	1.11
RC wage	1.00	1.00	1.25	1.14
RM wage	1.00	1.00	1.00	0.93
Wage premia				
NRC	1.36	1.31	1.84	1.80
NRM	0.62	0.63	0.69	0.74
RC	0.92	0.88	1.15	1.09
Variance of log wages	0.326	0.308	0.403	0.445
NRC	0.300	0.294	0.300	0.413
NRM	0.218	0.207	0.218	0.253
RC	0.260	0.253	0.260	0.358
RM	0.268	0.261	0.268	0.329

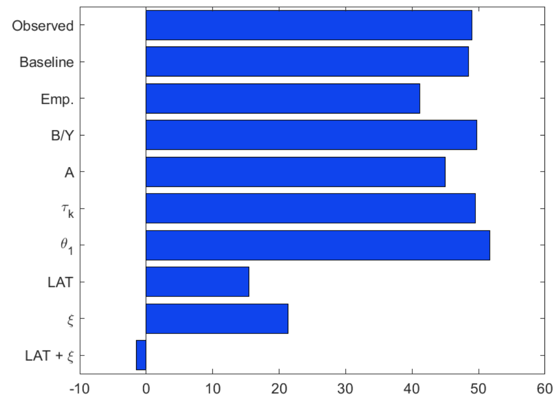
Note: The first section of the table indicates the relative input quantities. The second section indicates wages per efficiency unit by occupation (model definition) and wages per hour at constant 1968 prices by occupation (data definition). Both prices are normalized to 1 in 1980. The third section indicates the wage premia calculated as the ratio between the marginal productivities of the labor from each occupation category relative to RM in the case of the model. Wage premia calculation is described in Appendix B for the data.

75% of the total change in the aggregate earnings Gini.

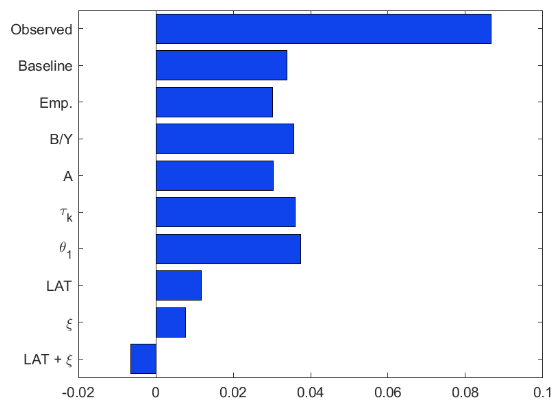
According to the model, the most significant single source of the variation in earnings dispersion is investment-specific technological change, as measured by the relative price of investment goods, ξ. By keeping this parameter at its 1980 value, the model produces only 11% of the change. In tandem, removing labor augmenting technological change leads to a 35% variation of the Gini index relative to its 1980 level. If we abstract from both these sources of technical progress, the dispersion predicted by the model drops, underlining the importance of the technology channel. By contrast, we estimate



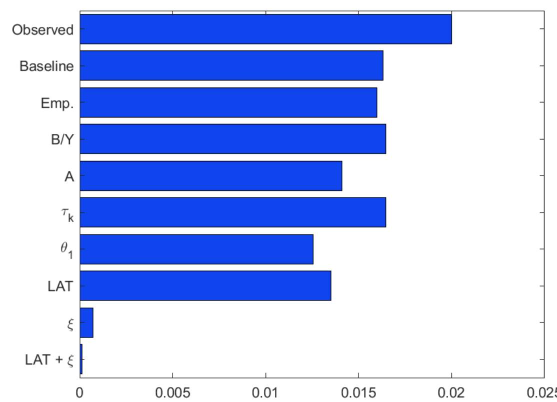
(a) Change in earnings Gini



(b) Change in NRC wage premium (p.p.)



(c) Change in wage Gini



(d) Change in labor supply Gini

Note: "Observed" indicates the change observed in the data. It is measured in percent for the earnings Gini and in percentage points for the NRC wage premium. "Baseline" indicates the change predicted in the theoretical model. Each of the remaining bars indicate the change in the model statistics resulting from keeping the corresponding parameters at their 1980 levels. "Emp" represents the impact of the location parameter of the distributions of idiosyncratic costs of entering a given occupation. "A" is total factor productivity. "LAT" is the set of labor augmenting technology indices. The remaining parameters are as per their previously indicated notation.

Figure 4: Decomposition of variation in dispersion measures from 1980 to 2015. Technological progress accounts for most of the changes in earnings inequality predicted by the model.

that changes in the progressivity of the labor income tax system and in the costs of acquiring skills had minimal impact in earnings dispersion in this period (11% and 0%, respectively).

Figure 4b shows the impact on the change in the non-routine cognitive wage premium, which displays the most significant variation when compared to the other occupations, and is the centerpiece of the mechanisms driving wage inequality in our model. Unsurprisingly, the model matches the variation in this premium nearly perfectly, given that it is parameterized using the estimates from the empirical production function.

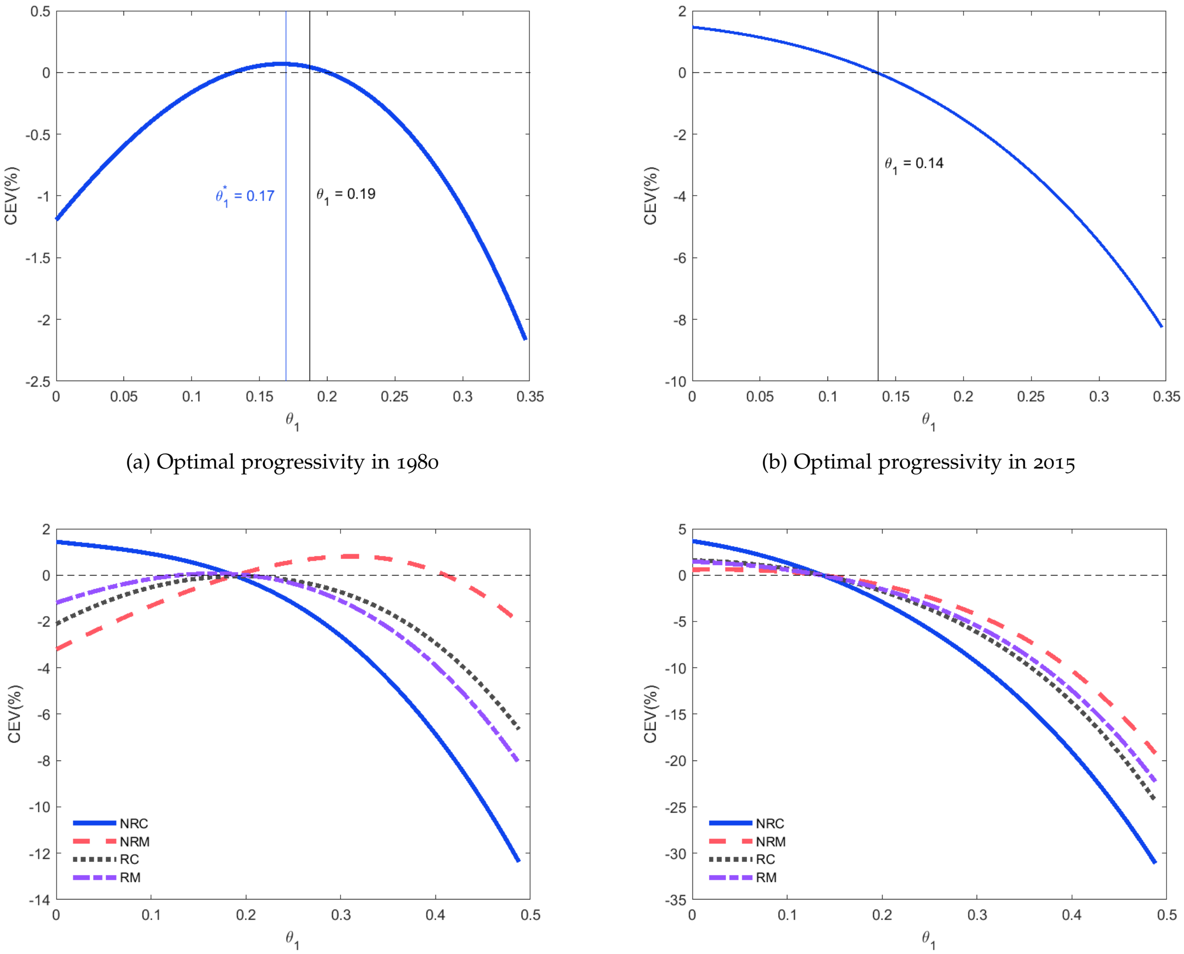
Figure 4c shows the model predictions for the wage Gini. Overall, our framework accounts for roughly 40% of the observed change in wage dispersion. This follows from our modeling choices: The central mechanism of the model crucially affects between-group inequality, rather than within-group. Table 6 shows how the variance of log hourly wages increased across all groups. This accounts for the more muted impact of the predictions of our model compared to the data.

Finally, Figure 4d shows the results for labor supply dispersion. In the data, the variation in the labor supply Gini is much more moderate when compared to wage and earnings. The theoretical model predicts 80% of this change, driven by the impact of technological progress and ISTC in particular.

6.2 Impact of technological change on optimal progressivity

In this section we show the model's predictions on optimal progressivity and how they change across time and occupations. The experiments in this section involve changing the progressivity parameter, θ_1, and measuring the impact in terms of consumption equivalent variation. To make these experiments compatible with the literature on optimal taxation, we use θ_0, the scale parameter of distortionary labor income taxation, as a clearing variable for the government budget constraint. In other words, θ_0 is such that the government is able to raise enough tax revenue to cover the level of government expenditure and lump sum transfers at the initial steady state. Expenses on public debt are allowed to vary between steady states.

The top panels of Figure 5 plot the social welfare functions for 1980 and 2015. In 1980, we estimate that actual progressivity stood slightly above its optimal value, which



(a) Optimal progressivity in 1980

(b) Optimal progressivity in 2015

(c) Welfare function by occupation in 1980

(d) Welfare function by occupation in 2015

Note: The top left panel plots social welfare as a function of the progressivity parameter, θ_1, for 1980, under the baseline calibration. Social welfare is measured as the consumption equivalent variation required for unborn agents to be indifferent between baseline and the new policy, without accounting for transitions. The vertical lines indicate current and optimal progressitivy levels. θ_1^* indicates optimal progressivity according to the model. The top right panel shows the same exercise for 2015. The bottom two panels show the social welfare functions for households starting their life in the indicated occupation categories in each year.

Figure 5: Optimal progressivity across time and occupations. Technological change implies lower optimal progressivity, as a result of rising return rates of capital and increasing wages for non-routine manual occupations.

we determine to be 0.17. This estimate is quite close to Heathcote et al. (2020), who put it at 0.18. Our estimated gains from changing θ_1 to its optimal value are quite low, at 0.07%.

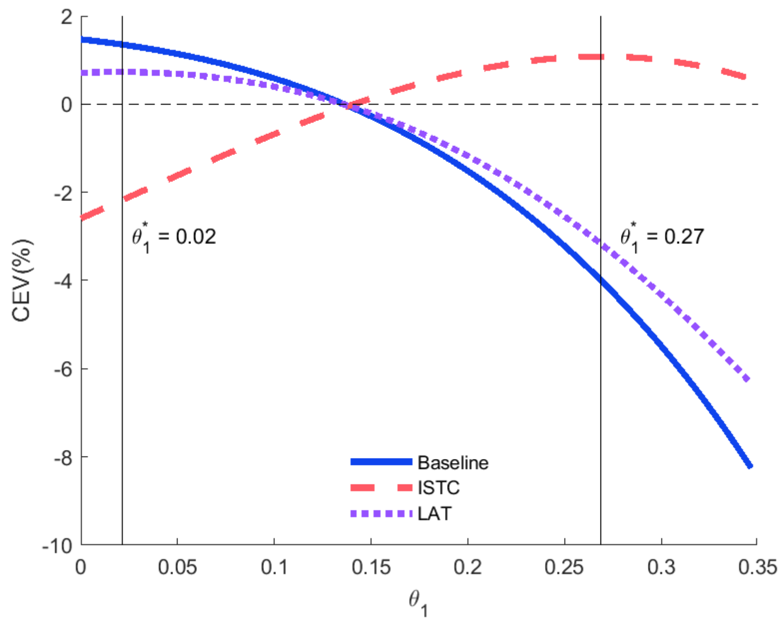
Figure 5c shows the decomposition of the welfare function by occupation category in

1980. The gains from adjusting progressivity are unevenly distributed among occupations, and reflect their position in the wage distribution. On one extreme lie non-routine cognitive occupations with the highest hourly wages and high complementarity with equipment capital. Households that choose to enter these occupations pay the highest marginal tax rates in the economy, and benefit significantly from lower progressivity. In particular, since this group owns the largest portion of wealth in the economy, taxing its wages leads to lower capital accumulation, which affects their wages due to complementarity with equipment. For this group, setting progressivity to zero would increase their welfare by close to 1.5%.

In the center of the distribution are the workers belonging to the routine manual and the routine cognitive occupations, which are closest to the median wage and are comparatively less affected by changes in progressivity in either direction. They also stand to gain much less from capital accumulation, given their low complementarity with capital equipment and its price in 1980.

Finally, workers in non-routine manual occupations lie at the bottom of the wage distribution and are thus more prone to benefit from increased progressivity of the labor income tax schedule. In 1980, setting θ_1 to 0.31 would improve welfare of NRM households by around 1%, if the economy were to move instantly to the new steady state.

The predictions of the model differ sharply for the 2015 economy, as shown in Figure 5b. In this case, the economy underwent significant technological progress, including a significant drop in the price of equipment capital. This latter development has three main consequences: First, hourly wage growth for all occupation categories save routine manual workers. Second, a surge in GDP per capita due to the lower price of equipment and greater incentive to accumulate capital. Third, rising return rates on capital. These three channels, which are underpinned by ISTC, lead to a leftward shift in the social welfare function. The optimal progressivity parameter is now lower than zero for the



Note: The solid blue line denoted "Baseline" indicates the social welfare function for the economy calibrated to 2015. The dashed red line denoted "ISTC" is the SWF of the economy calibrated to 2015 but where the relative price of investment goods is kept at its 1980 level. The dotted purple line denoted "LAT" is the SWF for the economy calibrated to 2015 but where labor augmenting technologies have been kept at their 1980 levels. θ^* indicates optimal progressivity according to the model for each experiment, except for 2015 which is zero.

Figure 6: Optimal progressivity in 2015 and the role of technological change. ISTC accounts for most of the leftward shift of the social welfare function.

whole economy, compared to an actual value of 0.14 in 2015.

This prediction stems from the relationship between technical change and investment: ISTC is an exogenous technological process, which must be incorporated into the production process via savings. This is unlike other sources of changes in productivity such as labor augmenting technology or TFP. Therefore, higher marginal tax rates at the top, by preventing the accumulation of capital equipment lower wage growth for all occupations which benefit from equipment-occupation complementarity. Overall, setting θ_1 to zero would increase welfare by roughly 1.5% if the economy were to instantly move to the new steady state.

Figure 5d shows the decomposition of welfare by occupations in 2015. In this case, all workers in the economy prefer a flat tax rate. In particular, workers in non-routine manual occupations now prefer no progressivity, save that which stems from the existing lump-sum transfer from the government. Still, the households which would benefit the most from a change in progressivity to its optimal level are the non-routine cognitive, which would see their welfare improve by roughly 4%, in contrast to the 2% for RM and RC, and the 1% increase for the non-routine manual.

In order to verify that ISTC plays a central role in these predictions, we compute the social welfare function for different scenarios of technological change. Figure 6 displays the impact of the different sources of occupation-biased technical change in the determination of the optimal policy.

The solid blue line indicates the SWF for the baseline calibration in 2015. In this case, optimal progressivity is lower than zero, as previously discussed. The dashed red line is the SWF in 2015, where the price of equipment is kept at its 1980 level. In this scenario, investment-specific technological change does not take place. Comparing to 1980, optimal progressivity rises from 0.17 to 0.27. This is the result of the increase of the labor-augmenting technology of non-routine cognitive occupations compared with all the other occupations, which experience a decline.

The dotted purple line indicates the SWF for the economy where ISTC took place, but where efficiency indices of all the occupations remained in their 1980 levels.

7 Conclusion

Since 1980 there has been a steady increase in earnings inequality alongside rapid technological growth in the U.S. economy. To what extent does technological change explain the observed increase in earnings dispersion? How does it affect the optimal progressivity of the tax system? To answer these questions, we develop a life-cycle, overlapping generations model with uninsurable idiosyncratic earnings risk, multiple sources of technological change, a detailed tax system, and occupational choice.

Calibrating the model to the U.S. we find that occupation-biased technological change can account for 90% of the increase in post-tax earnings Gini. The main driver is the rising relative wage of non-routine cognitive occupations, which benefit the most from complementarity with capital. However, we show that non-routine manual occupations, which have the lowest average wage, have also benefited from technological progress relative to routine occupations, which occupy the center of the wage distribution. For this reason, we find that optimal progressivity drops from 1980 to 2015, as lower paid occupations are relatively better off as a result of technological change.

A Data sets

A.1 CPS

Imputation. From survey year 1968 to 1975, hours worked in the previous year are not available. We follow Acemoglu and Autor (2011) and impute these by running a regression of hours worked on the previous year on hours worked in the current year, on an indicator variable for whether the individual worked 35+ hours last year or not, on the current labor force status, on an interaction variable between the two previous variables, and on the sector the individual worked in the previous year for the survey years 1976-1978. We then use the estimated equation to assign hours worked in the previous year to the 1968-1975 observations.

Weeks worked last year are not available for 1968-1975 also. We compute mean weeks worked last year by race and gender for the years 1976-78 for each bracket and impute those means for the 1968-1975 period.

Top-coding. To obtain accurate estimates of earnings inequality and wage premia, we have to account for the top-coding in the CPS earnings data. We use the variables *INCWAGE*, *INCLONGJ* and *OINCWAGE*, in the taxonomy of Flood et al. (2018). We proceed in two steps: (i) identify top-coded observations; (ii) assuming the underlying distribution is Pareto, we forecast the mean value of top-coded observations by extrapolating a Pareto density fitted to the non-top-coded upper end of the observation distribution. For details on the procedure to approximate the tail of a Pareto distribution see Heathcote et al. (2010).

Top-coding thresholds in the ASEC change across variables and time. Information on top-coding thresholds can be found on the IPUMS website. Prior to the 1996 survey year, there is little documentation available regarding the thresholds, but the effective top-coding thresholds are provided by IPUMS based on Larrimore et al. (2008). From 1996 onward, the Census Bureau began reporting top-coding thresholds for a set of income variables.

In addition, the Census Bureau has changed its top-coding procedure through time: from 1996 until 2011, the values for top-coded observations were replaced with values based on the individual's characteristics (so-called cell/group means). From 2011 onward, the Census Bureau shifted from an average-replacement value system to a rank proximity swapping procedure.

Ideally, we would like to use a consistent procedure for handling top-coding across time. However, since the Census Bureau started publishing top-coding procedures in 1996, they drastically reduced public use censoring thresholds. Heathcote et al. (2010) found that the Pareto-extrapolation procedure does not perform well in this case. Therefore, we only apply this procedure until survey year 1995. Heathcote et al. (2010) use the extrapolation until survey year 1999, but we find that this produces a large jump in earnings inequality in the late 90's which does not seem plausible.

Bottom-trimming. According to Flood et al. (2018), there is no publicly available information on bottom-coding thresholds of income variables in the ASEC. To deal with this shortcoming, a common practice in the literature is to select a bottom threshold on earnings for inclusion in the sample. We use the procedure of Heathcote et al. (2010): the final sample only includes observations where the hourly wage is above the minimum threshold of one half of the federal minimum wage in each year (end-year federal minimum wage data for farm and non-farm workers is retrieved from FRED).

Variable definitions. All variables are computed as explained in Acemoglu and Autor (2011).

Sample selection. We build two samples, labeled A and B. Table 7 shows the number of records at each stage of the selection process.

The initial sample is a cleaned version of the raw data, which excludes individual records which are either: below the age of 16 in the previous year, not part of the

Table 7: CPS sample selection (survey years 1968-2017)

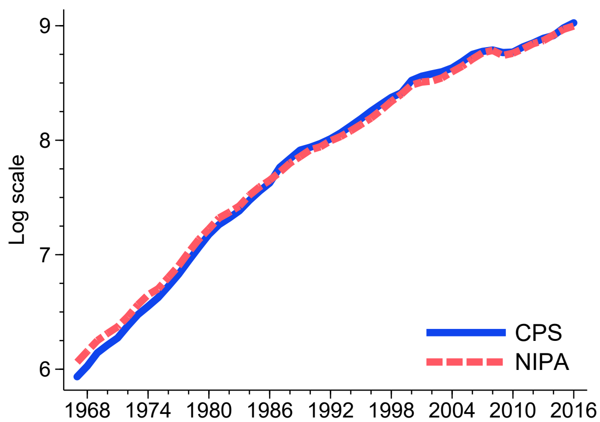
	Dropped	Remaining
Initial sample		**4,089,617**
Wage > 0.5 × min. wage	116,608	3,973,009
Sample A		**3,973,009**
Age 25-64	861,598	3,111,411
Hours worked per week last year > 6	19,308	3,092,103
Sample B		**3,092,103**

universe, not wage workers, did not work in the previous year, have zero or missing weights, missing age, or have positive earnings but no weeks worked in the previous year, or vice-versa. In 2014, two distinct samples were drawn because of sample redesign. We keep the sample which is consistent with previous surveys.

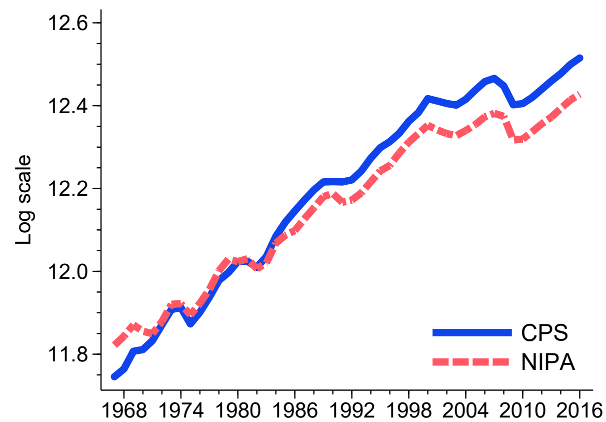
Sample A excludes all records where the hourly wage is lower than one half of the federal hourly minimum wage. We assume that this sample is representative of the (non-institutionalized) U.S. population. In order validate the data, we compare a set of sample statistics on wages and hours worked to their aggregate (NIPA) counterpart. This is shown on Figure A.1.

There is an average absolute deviation of 5% between the NIPA (Table 2.1, line 3) and the CPS wage bill. Regarding hours of part and full-time employees, the NIPA series (Tables 6.9B-D, line 2) is lower by 3.3%, on average, and 6.5% after 1986. The BEA uses BLS data to calculate its hours worked series, but the variables are based on the Quarterly Census of Employment and Wages (QCEW) data, rather than on the ASEC variable "usual hours worked per week last year" used in this paper. The total number of full- and part-time employees is much closer to the NIPA series (Table 6.4B-D, line 2), albeit the gap is still 2.7% on average.

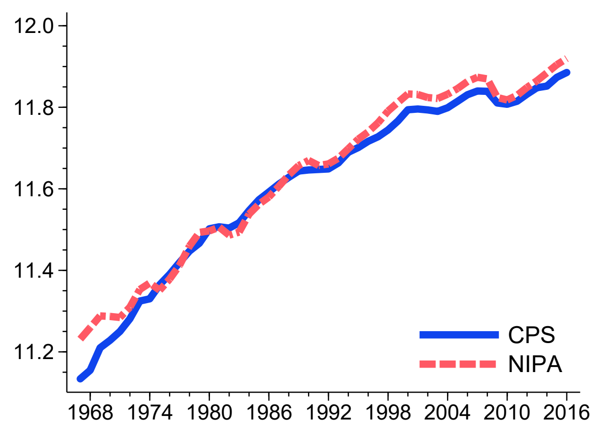
Sample B excludes individuals between 25 and 64 years old in the previous year. We consider that 25 years old is a reasonable cutoff age, where individuals' occupation



(a) Wages and salaries



(b) Employee full- and part-time hours



(c) Full and part-time employees

Figure A.1: Comparison between aggregate labor variables in the CPS and in the NIPA.

choice has stabilized. According to the BLS, for 2018 the labor force participation rate drops from 65% to 27%, on average, between the 55-64 and the 65 and older age brackets, which justifies our upper bound for inclusion in the sample. We also exclude records where individuals usually worked less than 6 hours per week in the previous year. This is the sample we use to calculate inequality and wage premia statistics. For comparison, Heathcote et al. (2010) have 2,578,035 individual records in their individual-level database, covering the 1967-2005 survey years. This implies that we have around 63,000 records per year, on average, while Heathcote et al. (2010) have 68,000.

B Measures

B.1 Labor supply and wages

We follow the procedure of Krusell et al. (2000) to build measures of wages and the labor supply for each of the labor categories (NRC, NRM, RC, RM). The sample used for this purpose is the same as the one used for the regression analysis described on section 2, apart from the fact that we include workers which did not work full-year or full-time. The reason for this is that in the regression analysis we were aiming to identify the wage premia by observing workers in a similar labor market situation. Here, the aim is to construct measures of labor inputs and wages which will be used in the estimation of the production function. We use these bins in order to exclude phenomena such as the increased labor force participation of women from the estimation. Since the labor supply of part-time workers contributes to real GDP, it is necessary to account for those. We do not, however, include self-employed individuals in the analysis. In what follows, the subscript t denotes the year and i denotes an individual observation.

For each worker we record the following variables: hours usually worked per week last year, weeks worked last year, earnings last year, potential experience, race, gender, years of education, occupation category and ASEC weight. Potential experience is divided into 5 five-year groups. Race into white, black and other. There are two sexes. Education is divided into 5 categories: no high school, high school graduate, some college, college graduate, and post college education. Occupation groups are defined as before.

Each worker is assigned to one group defined by the variables described. There are 600 groups, each one denoted by $g \in G$. For each group, we construct a measure of the labor input and labor earnings. The individual labor input is defined as $l_{it} = h_{it} wk_{it}$, where h_{it} is hours usually worked last year and wk_{it} is weeks worked last year. The individual wage is defined as $w_{it} = y_{it}/l_{it}$. Therefore for each group g we define:

$$l_{gt} = \frac{\sum_{i \in g} l_{it} \mu_{it}}{\mu_{gt}},$$

$$w_{gt} = \frac{\sum_{i \in g} w_{it} \mu_{it}}{\mu_{gt}},$$

where μ_{it} is the individual ASEC weight and $\mu_{gt} = \sum_{i \in g} \mu_{it}$. We aggregate the set G of 600 sets into the occupation categories previously defined $o \in \{\text{NRC}, \text{NRM}, \text{RC}, \text{RM}\}$. From this aggregation we obtain total annual labor input per group, $N_{o,t}$, and its hourly wage, $w_{o,t}$. We assume that the groups within a category are perfect substitutes, and for aggregation we use as weights the group wages of 1980. Thus, for each category o, we have:

$$N_{o,t} = \sum_{g \in s} l_{gt} w_{g80} \mu_{gt},$$

$$w_{o,t} = \frac{\sum_{g \in o} w_{gt} l_{gt} \mu_{gt}}{N_{o,t}},$$

where μ_{it} is the individual ASEC weight and $\mu_{o,t} = \sum_{i \in s} \mu_{it}$. This yields a measure of the total labor input in hours by category $(h_{\text{NRC},t}, h_{\text{NRM},t}, h_{\text{RC},t}, h_{\text{RM},t})$, as well as average hourly wages $(w_{\text{NRC},t}, w_{\text{NRM},t}, w_{\text{RC},t}, w_{\text{RM},t})$.

B.2 Capital, prices and output

Table 8 shows the definitions of main variables compared with those of Krusell et al. (2000).

Table 8: Comparison with Krusell et al. (2000)

Variable	Definition	Definition (KORV)
Output	Business non-farm gross value added	Private domestic product (excluding housing and farm)
Structures	Non-residential structures (private)	Non-residential structures (private)
Equipment	Equipment (private)	Non-military equipment (private)
Equipment price	Equipment price deflator (BEA)	Authors' calculations based on Gordon (1990)

Capital. Our main source for capital data are the BEA's fixed asset accounts and the NIPA. We use the method of Berlemann and Wesselhöft (2014) to construct measures of the capital stock at constant 2012 prices for equipment and non-residential structures. We only include private capital in our measure. Nominal investment for each asset category is deflated using the investment price index from the BEA. The resulting measures for non-residential structures ,$K_{e,t}$, and equipment capital, $K_{s,t}$. Like Krusell et al. (2000), we interpret these values as being measured in efficiency units.

Equipment prices. To obtain the price of equipment in each year, we aggregate investment price indices from the BEA fixed asset accounts (Table 5.3.4) across equipment types using a Törqvist index. We then divide the resulting average equipment price by the BLS consumer price index for all urban consumers to obtain the relative price of investment.

Depreciation rates. Obtained using the method by Eden and Gaggl (2018). We use BEA data on the net current cost of the stock of capital, $P_{it}\text{NetStock}_{it}$, and depreciation at current cost, $P_{it}\text{Dep}_{it}$, to compute depreciation rates, which are given by the following formula:

$$\delta_{it} = \frac{P_{it}\text{Dep}_{it}}{P_{it}\text{NetStock}_{it} + P_{it}\text{Dep}_{it}}.$$

We compute average depreciation rates for equipment and non-residential structures, with weights given by the capital stocks at constant prices.

Output. To measure output, we use real gross domestic product in chained 2012 US dollars, retrieved from FRED (FRED code: GDPCA; NIPA code: A191RX).

C Production function estimation method

To estimate the production function, we use the two-step SPML estimator proposed by Ohanian et al. (1997). First, we write the non-linear state space model formally. Next, we briefly describe the methods used to estimate it.

Our non-linear state-space system of equations is of the form:

$$\begin{aligned} &\text{Measurement equations :} \qquad && Z_t = f(X_t, \psi_t, \omega_t; \theta), \\ &\text{State equations :} && \psi_t = \psi_0 + \psi_1 t + \nu_t. \end{aligned}$$

$f(.)$ contains the labor share equation, the three wage bill equations and the no-arbitrage condition. Z_t is thus a (5×1) vector, which is a function of the variables X_t, the log of the unobservable labor quality indices ψ_t, which is a (4×1) vector, and ν_t and ω_t which are (5×1) and (4×1) vectors, respectively, of i.i.d. normally distributed disturbances. Like Krusell et al. (2000), we assume that A_{t+1} and ψ_{t+1} are known when investment decisions are made.

The model is estimated in two steps: (i) instrument the variables which are potentially endogenous; and (ii) apply the SPML estimator. We assume that the capital stocks, $K_{s,t}$ and $K_{e,t}$, are exogenous at date t. However, we allow for the possibility that date t values of the labor inputs may respond to realization of the technology and labor quality shocks. To instrument these variables, we run a first stage regression of the labor inputs on a constant, current and lagged equipment and non-equipment capital stocks, the lagged relative price of equipment, a trend and the lagged value of the OECD composite leading indicator of business cycles. $\tilde{X}_t$ is the vector of $K_{s,t}$, $K_{e,t}$, the instrumented values of the labor inputs, the depreciation rates and the capital income tax.

The SPML procedure is as follows. Given the distributional assumptions on the error terms, for each t we generate S realizations of the dependent variables, each indexed by

i, starting at $t = 1$ in two steps:

$$\text{Step 1}: \quad \psi_t = \psi_0 + \psi_1 t + \nu_t.$$
$$\text{Step 2}: \quad Z_t^i = f(\tilde{X}_t, \psi_t^i, \omega_t^i, \theta).$$

In Step 1, we draw a realization of ν_t from its distribution (conditional on our guess of Ω) and use it to construct a date t value for ψ_t. In Step 2, we use our realization of ψ_t, ψ_t^i, together with a draw of ω_t (conditional on our guess of η_ω), to generate a realization of Z_t, Z_t^i. By using this procedure to generate S realization, we can obtain first and second simulated moments, respectively, of Z_t:

$$m_S(\tilde{X}_t;\theta) = \frac{1}{S}\sum_{i=1}^{S} Z_t^i,$$
$$V_S(\tilde{X}_t;\theta) = \frac{1}{S-1}\sum_{i=1}^{S}\left(Z_t^i - m_S(\tilde{X}_t;\theta)\right)\left(Z_t^i - m_S(\tilde{X}_t;\theta)\right)'.$$

From this procedure, we will obtain $2T$ moments, which we will use to construct an objective function. Denoting the vector of all actual observations of the dependent variables by Z^T:

$$L_S(Z^T;\theta) = -\frac{1}{2T}\sum_{t=1}^{T}\left[[Z_t - m_S(\tilde{X}_t;\theta)]' V_S(\tilde{X}_t;\theta)^{-1}[Z_t - m_S(\tilde{X}_t;\theta)] \ln\det(V_S(\tilde{X}_t;\theta))\right].$$

The SPML estimator, $\tilde{\theta}_{ST}$, is the maximizer of this expression. It is very important that throughout the maximization procedure of the objective function the same set of ($T \times S$) random realizations of the dependent variables. Otherwise, the likelihood becomes a random function.

D Solution algorithm

To characterize the stationary competitive equilibrium of the model we must find the ratios $\frac{K_s}{N_{NRC}}$, $\frac{K_e}{N_{NRC}}$, $\frac{N_{NRM}}{N_{NRC}}$, $\frac{N_{RC}}{N_{NRC}}$, and $\frac{N_{RM}}{N_{NRC}}$ which clear the capital and labor markets. In addition, we have to fit the tax function, clear the government and social security budget and find the value of Γ which, given a distribution for the state variable h, uniformly distributes the assets of the dead among the living. The algorithm is as follows:

1. Make a guess on $\frac{K_e}{N_{NRC}}$, $\frac{N_{NRM}}{N_{NRC}}$, $\frac{N_{RC}}{N_{NRC}}$, and $\frac{N_{RM}}{N_{NRC}}$.

2. Obtain the value of $\frac{K_s}{N_{NRC}}$ which is consistent with the remaining ratios given the no-arbitrage condition 27 using a bisection method. Compute marginal productivities 16-20 with these guesses.

3. Guess ψ_{ss}, Γ and average earnings.

4. Compute value and policy functions for the retired and active agents by backward induction, given processes for the transitory and permanent shocks. Both shocks are discretized using the Tauchen procedure (Tauchen, 1986), with 4 and 20 states, respectively. We use 20 states for the permanent shock so that we have 5 states for each group supplying a different labor variety. This allows us to calibrate both within-group and between group earnings inequality. The grids for h and n have 24 and 100 points, respectively. In between the grid points, the values of the functions are interpolated using cubic splines.

5. Simulate the model for 120,000 agents, where assets holdings are zero for every agent entering the labor market. Obtain total savings (asset demand), $\int h + \Gamma d\Phi$, and quantities of each labor variety supplied, $N_{NRC}, N_{NRM}, N_{RC}, N_{RM}$.

6. Compute output given the labor supply of households. The quantity of government bonds is obtained by multiplying output by the government debt-to-GDP

ratio. The remainder of asset demand must be allocated between non-equipment and equipment capital. The quantity of structures is obtained by multiplying the initial guess of $\frac{K_s}{N_{NRC}}$ by the quantity of labor supplied by households N_{NRC}. The quantity of equipment, measured in consumption units, is the residual of asset demand. If this residual is negative, we set the quantity of equipment to be 10% of the guess for the non-equipment stock, which allows the algorithm to proceed.

7. Obtain implied values for ψ_{ss}, Γ and average earnings. Compare with guesses made in step 4. If the difference between guesses and implied values is within a preset tolerance interval, proceed to step 8. If not, update the guesses of each variable and go back to step 4.[12]

8. Compute the difference between the ratios implied by the labor supply and asset demand of households with the initial guesses. If these differences are within a preset tolerance level, the solution has been reached with sufficient accuracy. If not, update the guesses and go back to step 2.

[12]Our algorithm uses the homotopy procedure to update all the guesses. That is, if ν is the initial guess and ν' is the value implied by the simulation, then the updated guess is $\nu'' = \nu + a(\nu' - \nu)$, where a is a constant chosen by the researcher which controls the size of the update and the rate of convergence of the algorithm.

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