Investment-Specific Technological Change, Taxation and Inequality in the U.S.

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Investment-Specific Technological Change, Taxation and Inequality in the U.S.*

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Abstract

Since 1980 the U.S. economy has experienced a large increase in income inequality. To explain this phenomenon we develop a life-cycle, overlapping generations model with uninsurable labor market risk, a detailed tax system and investment-specific technological change (ISTC). We calibrate our model to match key characteristics of the U.S. economy and study how ISTC, shifts in taxation, government debt and employment have contributed to the rise in income inequality. We find that these structural changes can account for close to one third of the observed increase in the post-tax income Gini. The main mechanisms in play are the rise in the wage premium of non-routine workers, resulting from capital-non-routine complementarity, as well as a reduction of the progressivity of the labor income tax schedule, which increases post-tax inequality. We show that ISTC alone accounts for roughly 15% of the change observed in post-tax income Gini, while the reduction in progressivity accounts for 16%.

Keywords: Income Inequality, Taxation, Automation

JEL Classification: E21; H21; J31;

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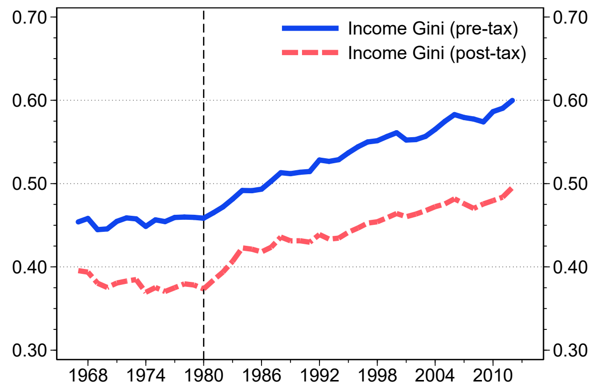
1 Introduction

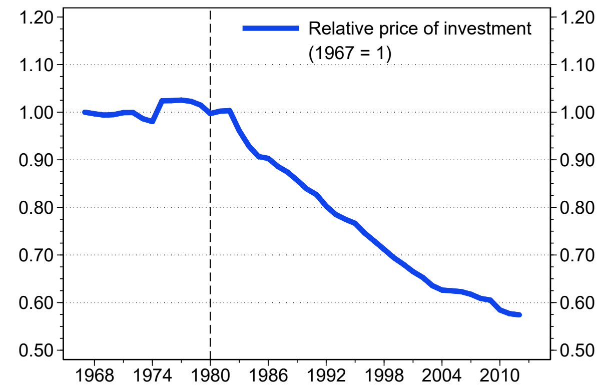
There has been a steady rise in income inequality in the U.S. since 1980. Figure 1 shows that this phenomenon occurred in tandem with a fall in the relative price of investment, which can be viewed as reflecting investment-specific technological change (Krusell et al., 2000; Karabarbounis and Neiman, 2014), and a sharp reduction in tax progressivity (Ferriere and Navarro, 2018). In this paper, we use an incomplete markets model calibrated to the U.S. economy to study how each of these factors has influenced the rise in income inequality.

We design an overlapping generations model featuring investment-specific technological change, a detailed tax schedule, uninsurable idiosyncratic earnings risk, and incomplete markets. To generate factor-biased technological change, we assume some agents are born with abilities that are complement to capital while others are born with abilities that are substitute to capital. These distinct labor varieties are called routine and non-routine, respectively. We incorporate an additional dimension to the analysis of labor varieties by dividing workers into the skilled/unskilled categories. This allows us to take into account the rise in the skill premium (Krusell et al., 2000), and to analyze how the different categories of workers are affected by the selected structural changes. This is close to the spirit of Acemoglu and Restrepo (2017a), although, to our knowledge, we are the first to simultaneously include these two dimensions in standard incomplete markets model.

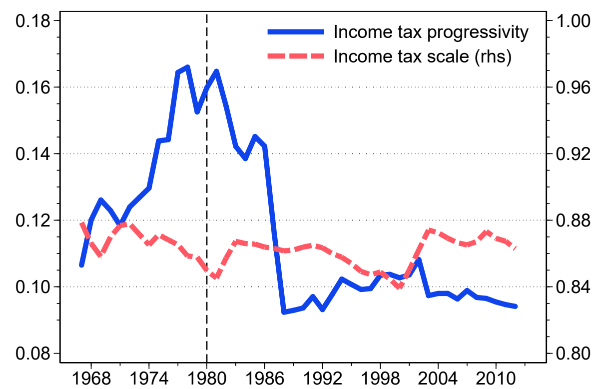
Aside from the direct impact of a fall in tax progressivity on income dispersion, the main mechanism at work in our model is the rise in the wage premium of non-routine workers, following a drop in investment prices. This is the result of the complementarity between capital and non-routine labor. As investment prices fall, capital accumulation becomes cheaper and firm demand for routine labor drops, along with wages. In contrast, non-routine labor becomes a more productive input, raising wages and labor demand for those workers.



(a) Inequality



(b) Investment good prices



(c) Taxation

Figure 1: Inequality, technology and taxation. Notes: Gini indices are from the World Inequality Database (WID). The relative price of investment is computed as the ratio between the price indices of non-residential investment and consumption goods, which are normalized to 1 in 1964. The series are obtained from the Bureau of Economic Analysis (BEA) National Income Accounts Table 1.1.4. The income tax progressivity is computed using the method in Ferriere and Navarro (2018). The income tax scale parameter is obtained from the marginal tax rate formula in Ferriere and Navarro (2018).

We find that ISTC and the fall in tax progressivity jointly account for at least one third of the increase in the income Gini coefficient. In particular, by means of counterfactual exercises we show that ISTC alone accounts for roughly 15% of the change in model post-tax income Gini, while the reduction in progressivity accounts for 16%. Other structural changes, such as the increase in non-routine relative employment, and social security taxes dampen these mechanisms by reducing the marginal productivity of non-routine labor and increasing the progressivity of the tax system.

The rest of the paper is organized as follows. Section 2 surveys the streams of literature to which this paper is related. In Section 3, we discuss the stylized facts that underlie our modeling choice. In Section 4, we describe the model. In Section 5, we show the calibration strategy. In Section 6, results are presented. Section 7 concludes.

2 Related Literature

This paper is related to the literature which documents a reduction in the labor share of income as a result of a fall in investment prices. Karabarbounis and Neiman (2014) show that the labor share has been declining across countries at least since the early 1980s. Using a general equilibrium model to obtain an expression for the labor share as a function of the price of investment goods, they are able to account for half of the observed decline in the labor share.

Eden and Gaggl (2018) estimate that the labor share in the U.S. has dropped by 6.8 percentage points since 1950. This drop was concurrent to a reduction in routine occupations, and of the price of information and communication technology (ICT) capital goods. Using a mechanism similar to Karabarbounis and Neiman (2014), they estimate that the drop in ICT capital prices accounts for half of the drop in the labour share.

The key ingredient that generates a contraction of the labour share in these models is the substitutability between capital and unskilled or routine labour in the production function, in the tradition of Krusell et al. (2000). This feature, coupled with a reduction in investment good prices, leads firms to substitute away from labour and towards capital. Our main mechanism is similar to that of Karabarbounis and Neiman (2014) and Eden and Gaggl (2018), but our focus are the distributional aspects which they abstract from in analyzing the effects of the drop in investment prices.

This paper is related to the heterogeneous agents literature which quantifies the effect of structural changes in the income and wealth distributions. In particular, Hubmer et al. (2017), which investigate the change in the wealth distribution in the U.S. as a result of changes in taxation. Similarly, Civale (2016) quantifies the impact that ISTC has produced on the wealth distribution. In contrast to these recent contributions, our focus is on the income distribution and on nesting these competing mechanisms on a single model, in order to evaluate their relative contributions.

Our paper is also related to the literature on the effects of automation (Autor et al., 2003; Michaels et al., 2010; Acemoglu and Restrepo, 2017a; Acemoglu and Restrepo, 2017b; Guerreiro et al. (2017); Acemoglu and Restrepo, 2018). Autor et al. (2003) document that computer capital substitutes for workers in performing cognitive and manual tasks, and complements workers in performing non-routine problems-solving. They argue that these features can account for a substantial fraction of the resulting shift in demand toward college-educated labor. Michaels et al. (2010) use cross-country industry level data to analyze the demand across skill levels and conclude that industries with faster ICT growth had greater increases in relative demand for high skill workers and larger falls in relative demand for middle skill workers. They find that there is little effect on low-skilled workers mainly performing routine tasks.

In string of recent papers Daron Acemoglu and Pascual Retrepo have both contributed to measuring the effects of automation and formalized them into a task-based model of the labor market. Acemoglu and Restrepo (2017b) investigate the impact of a greater robot usage in the US local labor markets. Their findings indicate large and robust negative effects on employment and wages. Acemoglu and Restrepo (2018) develop a theoretical framework where automation produces two competing effects on wages and labor demand: a displacement effect resulting from the substitution of labor for machines, reducing the demand for labor and wages; a productivity effect which is the product of cost-savings generated by automation, which increases the demand for labor in the remaining tasks.

In the model of Guerreiro et al. (2017) routine jobs performed by low skill agents can be taken over by automation units. As the marginal cost of producing robots changes across steady states, routine labor wages and employment change in the same direction, given the assumption of substitutability. They study the problem of optimal taxation and find that it is optimal for the government to provide a lump sum rebate financed by taxes on automation units. This result follows from an information asymmetry problem (in the spirit of Mirrlees, 1971), whereby the social planner cannot distinguish between routine or cognitive workers and is thus unable to condition transfers on individuals' types. Our paper contributes to this literature by analyzing the macroeconomic impact of these mechanisms and quantitatively accounting for their effects on income inequality in the US economy.

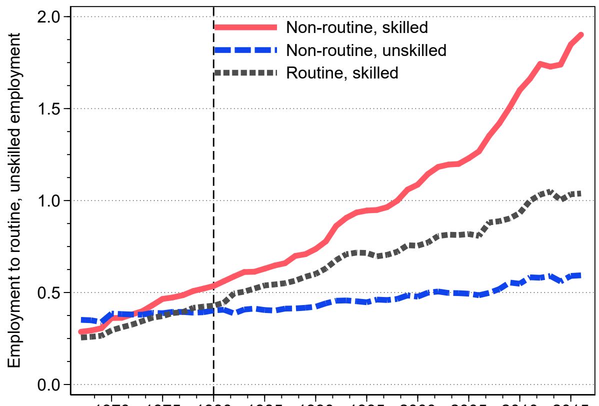
To dilute the perceived social cost of these trends several policies have been suggested, including a proposal famously put forth by Bill Gates to tax robots and "even slow down the speed [of automation]" (Delaney, 2017). The issue of optimal capital taxation has been discussed extensively since the 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.

3 Data

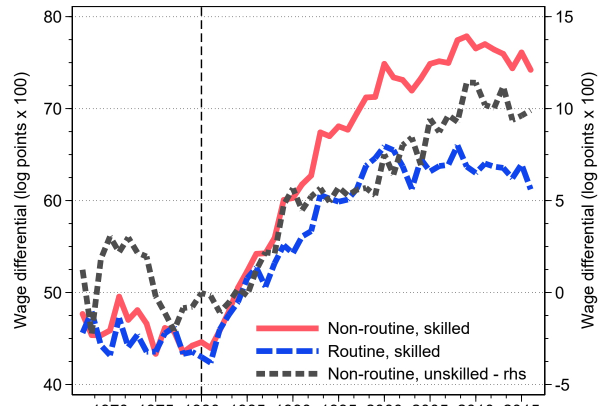
Our analysis of the U.S. labor market is carried out along two dimensions which have been found to be relevant when discussing the effects of technological change (Autor et al., 2003): (i) the nature of the tasks involved, i.e., whether they are susceptible to automation (routine) or not (non-routine); (ii) skill level, i.e., whether workers are college-educated or not. We combine these two dimensions were into four mutually exclusive groups: non-routine skilled (NRS) workers, non-routine unskilled (NRU) workers, routine skilled (RS) workers and routine unskilled (RU) workers. We use data from the Bureau of Labor Statistics (BLS) 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 used the Annual Social and Economic Supplement from the March CPS survey available from Flood et al. (2018), which contains data on yearly earnings and weeks 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. (2016) to categorize each worker into either routine and non-routine occupations. This is the so-called "consensus" classification scheme of Autor and Acemoglu (2011). Our division into skilled/unskilled is also that of Autor and Acemoglu (2011), where skilled workers are defined as those with at least one year of college. The population of interest is the set of non-military, non-institutionalized individuals aged 16 to 70, working full time, full year in the previous year, excluding self-employed and farm sector workers.

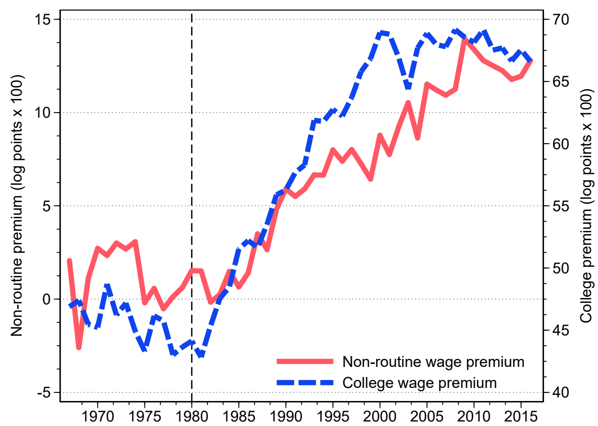
These data are used to construct series on group employment counts, raw wage differentials, and wage premia associated with skill and task type. To calculate the wage premia we use the method of Autor and Acemoglu (2011). Concretely, we run yearly cross sectional regressions of weekly log wages on task type, race (black, non-white other), potential experience in years, education, and interactions between education and experience up to the forth order separately for each gender. We then construct a set of bins for every combination of gender/race/work experience/task type/education level with constant weights for every period, defined as the average weight of a given group on total employment. The regression is used to predict the log-wage for each group in each year. Wage premia are defined as the log-difference in predicted wages between two groups whose only difference is either task type or skill level. The variables used are described on Appendix A.



(a) Relative employment levels



(b) Group wage differentials



(c) Wage premia

Figure 2: The rise of non-routine skilled labor. Notes: Wage differentials are obtained as the log difference between the average wage of each group. Groups for wages are constructed with using a constant composition of individual observable characteristics (experience, education, etc). Wage statistics are for males.

Figure 2 shows the evolution of employment and wages for the selected groups. We can discern four main stylized facts: (i) the strong performance of NRS workers compared to other groups and, in particular, RU workers; (ii) the strong growth of skilled worker groups relative to unskilled; (iii) the rise of the skilled and non-routine skilled premia. Our estimate of the skill premium has leveled off since 2000, informing our decision to focus our modeling efforts on the routine/non-routine dimension. To the best of our knowledge, we are the first to present estimates of both the skill and the non-routine wage premia which are orthogonal to each other.[1]

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 (2017b), 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 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 (2017b) 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.[2] 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.[3] 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

[1] Eden and Gaggl (2018) do not show their estimate of the skill wage premium.

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

[3] 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.

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.

4 Model

The model is an incomplete markets economy with heterogeneous agents and partial uninsurable idiosyncratic risk that is able to generate both income and wealth distributions. There are two types of households – non-routine and routine – that derive utility from non-durable consumption and leisure. The non-routine households are born with certain abilities, such as creativity, that allow them to perform tasks that are complement to capital. Routine households, on the other hand, are born with abilities that allow them to perform tasks that are substitute to capital. Each type of households face an idiosyncratic uninsurable stream of earnings in the form of wages, and make joint decisions about consumption, savings and hours worked. We further divide household types into skilled and unskilled, in order to assign the wage differentials observed in the data and the employment weights.

For the production side of the economy, we draw heavily on the modeling strategy in Krusell et al. (2000) and Karabarbounis and Neiman (2014). We assume the existence of a two-sector economy of consumption and investment goods. This formulation allows us to express the price of investment goods as a function of the level of technology in that sector relative to the consumption goods sector. We use a production function which embeds complementarity between capital and the non-routine labor variety, very similar to the one used in Karabarbounis and Neiman (2014). The asset structure used follows the same framework of Krusell et al. (2010), in order include investment prices in the household decision.

Demographics

We assume the economy is populated by a set of $J-1$ overlapping generations, as in Brinca et al. (2016). A household starts his life at age 20 and after retiring at age 65 households face an age-dependent probability of dying, $\pi(j)$, dying with certainty at age 100. 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). $\omega(j) = 1 - \pi(j)$ 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 $\Omega_j = \prod_{i=45}^{i=j} \omega(i)$. There are no annuity markets, so that 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. (2018) and Brinca et al. (2019).

Households also differ across persistent idiosyncratic productivity shocks, permanent ability, asset holdings, and a discount factor assuming three distinct values $\beta \in \{\beta_1, \beta_2, \beta_3, \beta_4\}$, which are uniformly distributed across agents. Working age agents have to choose how much to work, n_t, how much to consume, c_t, and how much to save, k_{t+1}, to maximize their utility. Retired households have consumption and saving decisions and receive a retirement benefit, Ψ_t.

Prior to joining the labor market agents draw from a uniform distribution with thresholds p_1, p_2, p_3 to determine which group they belong to. Groups are ordered in the following way: NRS, NRU, RS, RU. Therefore, an agent enters the NRS market if its draw is no greater than t_1. Each group is assigned a fixed effect over the routine unskilled, a_1, a_2, a_3, which is used to calibrate the inequality between groups. The aim of this setting is to accommodate, in a reduced form manner, the coexistence of occupation type and skill level in each of these markets, where only the occupation type actually enters the production function.

Labor income

Labor productivity depends on three distinct elements which determine the number of efficiency units each household is endowed with in each period: age j, labor group a, and an idiosyncratic productivity shock, u, which we assume follows an AR(1) process:

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

Thus, household i's wage is given by:

$$w_{i,t}(j, a, u) = w_{i,t}^s e^{\gamma_1 j + \gamma_2 j^2 + \gamma_3 j^3 + a_{i,t} + u_{i,t}}, \quad s \in \{NR, R\}, \tag{2}$$

where γ_1, γ_2 and γ_3 are calibrated directly from the data to capture the age profile of wages. Households' labour income depends on the wage per efficiency unit of labor w^s, $s \in \{NR, R\}$, where s stands for the labor variety that is supplied by the individual, either non-routine or routine, respectively.

Preferences

The utility of households, $U(c_t, n_t)$, is increasing in consumption and decreasing in work hours, $n_t \in (0, 1]$, and is defined as:[4]

$$U(c_t, n_t) = \frac{c_t^{1-\lambda}}{1-\lambda} - \chi \frac{n_t^{1+\eta}}{1+\eta}. \tag{3}$$

[4]We assume that labour disutility depends only on the level of supply, not on skill type.

Retired households' utility function has one extra term, as they gain utility from the bequest they leave to living generations:

$$D(h'_t) = \varphi \log(h'_t). \tag{4}$$

Technology

Consumption and investment goods are produced by means of transforming intermediate inputs using a linear production technology. All payments are made in terms of 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:

$$C_t + G_t = z^c_t, \tag{5}$$

where z^c_t is the quantity of input, purchased at p^z_t from a representative intermediate goods firm. Given that the final consumption good is competitively produced, its price equals the marginal cost of production:

$$P^C_t = 1 = p^z_t. \tag{6}$$

Investment goods firms operate in the same competitive environment. The production of X_t, the investment good, uses the transformation technology:

$$X_t = \left(\frac{1}{\xi_t}\right) z^x_t, \tag{7}$$

where $z^x_t(z)$ is the quantity of input z used in the production of the final investment good. ξ_t is the level of technology used in the production of X_t relative to the final consumption good. As ξ_t declines, the relative productivity in assembling the investment good increases. We assume that ξ_t evolves exogenously in this economy. We obtain the price of the investment good from the zero profit condition:

$$P_t^X = \xi_t p_t^z = \xi_t, \tag{8}$$

where $\xi_t = P_t^X / P_t^C$ is interpreted as the relative price of the investment good.

An representative intermediate goods firm produces input quantity $z_t^c + z_t^x$ using a constant returns to scale technology in capital and labor inputs, $y_t(z) = F(k_t(z), n_t^{NR}(z), n_t^R(z))$. It rents capital at rate r_t and labour at w_t^{NR} and w_t^R for non-routine and routine labour, respectively. Aggregate demand measured in terms of the consumption good, $Y_t = C_t + G_t + \xi_t X_t$, is taken as given. Firms choose labor and capital inputs each period in order to maximize profits:

$$\Pi_t^z = p_t^z y_t - r_t K_t - w_t^{NR} n_t^{NR} - w_t^R n_t^R, \tag{9}$$

subject to:

$$y_t = z_t^c + z_t^x = C_t + G_t + \xi_t X_t = Y_t. \tag{10}$$

Firm maximization implies that $p_t^z = P_t^C = 1$, $N_t^s(z) = N_t^s, \forall s,\ z_t^c = C_t + G_t$, $z_t^x = \xi_t X_t$, $y_t = Y_t = C_t + G_t + \xi_t X_t$, and $Y_t = F(K_t, N_t^{NR}, N_t^R)$, where K_t, N_t^{NR}, N_t^R are the aggregate values of capital and the labor varieties. We assume that the production function of the intermediate goods firm takes the following functional form:

$$Y_t = F(K_t, N_t^{NR}, N_t^R) = A_t \left(\phi_1 Z_t^{\frac{\sigma-1}{\sigma}} + (1-\phi_1) N_t^{R,\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{11}$$

$$Z_t = \left(\phi_2 K_t^{\frac{\rho-1}{\rho}} + (1-\phi_2) N_t^{NR,\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \tag{12}$$

where A_t is total factor productivity, ϕ_1 and ϕ_2 are factor shares, ρ is the elasticity of substitution between capital and non-routine labor, and σ is the elasticity of substitution between the composite of those factors and routine labor. In a competitive equilibrium firms set marginal products equal to factor prices:

$$r_t = \left[A_t^{\sigma-1}Y_t\right]^{\frac{1}{\sigma}} \phi_1 Z_t^{\frac{\sigma-\rho}{\rho\sigma}} \phi_2 \left(\frac{1}{K_t}\right)^{\frac{1}{\rho}}, \tag{13}$$

$$w_t^{NR} = \left[A_t^{\sigma-1}Y_t\right]^{\frac{1}{\sigma}} \phi_1 Z_t^{\frac{\sigma-\rho}{\rho\sigma}} (1-\phi_2) \left(\frac{1}{N_t^{NR}}\right)^{\frac{1}{\rho}}, \tag{14}$$

$$w_t^{R} = (1-\phi_1)\left(\frac{A_t^{\sigma-1}Y_t}{N_t^R}\right)^{\frac{1}{\sigma}}. \tag{15}$$

The capital law of motion is:

$$K_{t+1} = (1-\delta)K_t + X_t, \tag{16}$$

where X_t is aggregate gross investment and δ is the depreciation rate.

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_t.

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

$$y_a = 1 - \theta_0 y^{-\theta_1}, \tag{17}$$

where θ_0 and θ_1 define the level and progressivity of the tax schedule respectively, y is the pre-tax labour income and y_a is the after tax labour income.[5]

Tax revenues from consumption, income and capital taxes are used to finance public

[5] See the Holter et al. (2014) for a more detailed discussion of the properties of this tax function.

consumption of goods, G_t, public debt interest expenses, $R_t B_t$, and lump sum transfers, g_t. Denoting social security revenues by R_t^{ss} and the other tax revenues as T_t, the government budget constraint is defined as:

$$g_t \left(45 + \sum_{j \geq 45} \Omega_j\right) = T_t - G_t - R_t B_t, \tag{18}$$

$$\Psi_t \left(\sum_{j \geq 45} \Omega_j\right) = R_t^{ss}. \tag{19}$$

Asset Structure

Households may hold two types of assets: capital, k and government bonds, b.[6] There is no investment-specific technological change in the steady state, i.e., $\xi' = \xi$. The return rate on the bond must satisfy:

$$\frac{1}{\xi}\left(\xi + (r - \xi\delta)(1 - \tau_k)\right) = 1 + R(1 - \tau_k), \tag{20}$$

which follows from non-arbitrage: investing in capital must yield the same return as investing the same amount in bonds. The state variable for the consumer is:

$$h \equiv [\xi + (r - \delta\xi)(1 - \tau_k)]k + (1 + R(1 - \tau_k))b. \tag{21}$$

Using 20, in equilibrium we can re-write the previous equation as:

$$h = \frac{1}{\xi}[\xi + (r - \delta\xi)(1 - \tau_k)]\left(\xi k + b\right), \tag{22}$$

where we define $q \equiv \xi / \left[\xi + (r - \delta\xi)(1 - \tau_k)\right]$.

[6] In what follows, we suppress time subscripts for simplicity and use prime (′) to denote next period values of a variable.

Household Problem

On any given period a household is defined by age, j, asset position h, time discount factor $\beta \in \{\beta_1, \beta_2\}$, permanent ability a, a persistent idiosyncratic productivity shock u, and a time-constant ability to supply a given labor variety $s \in \{NR, R\}$. A working-age household chooses consumption, c, work hours, n, and future asset holdings, h', to solve his optimization problem. The household budget constraint is given by:

$$c(1+\tau_c) + \xi k' + b' = (\xi + (r - \delta\xi)(1-\tau_k))k + (1 + R(1-\tau_k))b + \Gamma + g + Y^N, \quad (23)$$

where Y^L is the household's labor income after social security and labour income taxes. Using 21 and 22 we can rewrite the budget constraint as:

$$c(1+\tau_c) + qh' = h + \Gamma + g + Y^N. \quad (24)$$

The household problem can then be formulated recursively as:

$$\begin{aligned}
&V(j,h,\beta,a,u) = \max_{c,n,h'} \left[U\left(c,n\right) + \beta \mathbb{E}_{u'}\left[V(j+1,h',\beta,a,u')\right]\right] \\
&\text{s.t.:} \\
&c(1+\tau_c) + qh' = h + \Gamma + g + Y^N \\
&Y^N = \frac{nw\left(j,a,u\right)}{1+\tilde{\tau}_{ss}} \left(1 - \tau_{ss} - \tau_l\left(\frac{nw\left(j,a,u\right)}{1+\tilde{\tau}_{ss}}\right)\right) \\
&n \in [0,1], \quad h' \geq -\underline{h}, \quad h_0 = 0, \quad c > 0,
\end{aligned}$$

The problem of a retired household differs on three dimensions: age dependent probability of dying $\pi(j)$, the bequest motive $D(h')$, and labour income, which is replaced by retirement benefits. Therefore, the retired household's problem is defined as:

$$V(j,h,\beta) = \max_{c,h'} \left[U\left(c,n\right) + \beta(1-\pi(j))V(j+1,h',\beta) + \pi(j)D(h') \right]$$

s.t.:

$$c(1+\tau_c) + qh' = h + \Gamma + g + \Psi$$

$$h' \geq -\underline{h}, \quad c > 0.$$

Stationary Recursive Competitive Equilibrium

$\Phi(j,h,\beta,a,u)$ is the measure of agents with corresponding characteristics (j,h,β,a,u). The stationary recursive competitive equilibrium is defined by:

1. Taking factor prices and initial conditions as given, the value function $V(j,h,\beta,a,u)$ and the policy functions, $c(j,h,\beta,a,u)$, $h'(j,h,\beta,a,u)$, and $n(j,h,\beta,a,u)$ solve the household's optimization problem.

2. Markets clear:

$$[\xi + (r - \xi\delta)(1-\tau_k)]\left(K + \frac{1}{\xi}B\right) = \int h + \Gamma \, d\Phi,$$

$$N^{NR} = \int_{a>a^*} n \, d\Phi,$$

$$N^{R} = \int_{a\leq a^*} n \, d\Phi,$$

$$C + \xi X + G = Y.$$

3. Firms set marginal products equal to factor prices:

$$\begin{aligned} r &= \left[A^{\sigma-1}Y\right]^{\frac{1}{\sigma}} \phi_1 Z^{\frac{\sigma-\rho}{\rho\sigma}} \phi_2 \left(\frac{1}{K}\right)^{\frac{1}{\rho}}, \\ w^{NR} &= \left[A^{\sigma-1}Y\right]^{\frac{1}{\sigma}} \phi_1 Z^{\frac{\sigma-\rho}{\rho\sigma}} (1-\phi_2) \left(\frac{1}{N^{NR}}\right)^{\frac{1}{\rho}}, \\ w^{R} &= (1-\phi_1) \left(\frac{A^{\sigma-1}Y}{N^R}\right)^{\frac{1}{\sigma}}. \end{aligned}$$

4. The government budget balances:

$$g \int d\Phi + G + RB = \int \left(\tau_k(r/\xi - \delta) \left(\frac{h+\Gamma}{\xi + (r-\xi\delta)(1-\tau_k)}\right) + \tau_c c + n\tau_l \left(\frac{nw(a,u,j)}{1+\tilde{\tau}_{ss}}\right)\right) d\Phi.$$

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 dead are uniformly distributed among the living:

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

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 1 lists parameter values and sources.

Table 1: 1980 Calibration Summary

Description	Parameter	Value	Source
Preferences			
Inverse Frisch elasticity	η	1.000	Brinca et al. (2016)
Risk aversion parameter	λ	1.000	Brinca et al. (2016)
Labor productivity			
Parameter 1 age profile of wages	γ_1	0.265	Brinca et al. (2016)
Parameter 2 age profile of wages	γ_2	-0.005	Brinca et al. (2016)
Parameter 3 age profile of wages	γ_3	0.000	Brinca et al. (2016)
Variance of idiosyncratic risk	σ_ϵ	0.307	Brinca et al. (2016)
Persistence idiosyncratic risk	ρ_u	0.335	Brinca et al. (2016)
NRS % wage difference	a_1	0.484	CPS
NRU % wage difference	a_2	-0.251	CPS
RS % wage difference	a_3	0.105	CPS
NRS weight	p_1	0.226	CPS
NRU weight	p_2	0.170	CPS
RS weight	p_3	0.181	CPS
Technology			
Depreciation rate	δ	0.060	Brinca et al. (2016)
Share of the composite	ϕ_1	0.516	Authors' calculations
Share of capital	ϕ_2	0.654	Authors' calculations
EOS routine/composite	ρ	5.628	Authors' calculations
EOS non-routine/capital	σ	0.827	Authors' calculations
Total factor productivity	A	1.000	Normalization
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	Ferriere and Navarro (2018)
Tax progressivity parameter	θ_1	0.160	Ferriere and Navarro (2018)
Government debt to GDP	B/Y	0.320	FRED
Military spending to GDP	G/Y	0.050	World Bank
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

Preferences

There has been a considerable debate in the literature on the value of the Frisch elasticity of labor supply, η, with estimates ranging from 0.5 to 2 or higher. We set it to 1.0, as in Brinca et al. (2016). Discount factors, disutility from work and the borrowing limit are calibrated by SMM and are discussed below.

Labor productivity

The wage profile through the life cycle (see equation 2) is calibrated directly from the data. We run the following regression, using Panel of Study of Income Dynamics (PSID) data:

$$\ln(w_i) = \ln(w) + \gamma_1 j + \gamma_2 j^2 + \gamma_3 j^3 + \varepsilon_i. \tag{25}$$

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 wage differential of each group, a, is calibrated to match the log difference in average wages between groups in 1980. The employment level of each group, which is equal to the probability of being born into a given group, is set to equal its observed weight in total employment in 1980.

Technology

We use the method by Eden and Gaggl (2018) to estimate the parameters of the production function, described in appendix B. Both total factor productivity and the relative price of investment are set to unity in 1980.

Government Budget and Social Security

As described before, to capture the progressivity of both the tax schedule and government transfers, we use the same labor income tax function as Benabou (2002) (equation 17). To estimate θ_0 and θ_1 in 1980 we use the method in Ferriere and Navarro (2018).

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, $\tau_c = 0.05$, $\tau_k = 0.47$.

Parameters calibrated using SMM

To calibrate the parameters that do not have any direct empirical counterparts, φ, β_1, β_2, β_3, β_4, $\underline{h}$ and χ, we use the simulated method of moments so that we minimize the following loss function:

$$L(\varphi, \beta_1, \beta_2, \beta_3, \beta_4, \underline{h}, \chi) = ||M_m - M_d|| \tag{26}$$

with M_m and M_d being the moments in the data and in the model respectively.

Given that we have seven parameters, we need seven data moments to have an exactly identified system. The seven moments we target in the data are the ratio of the average net asset position of households 65 and above relative to the average asset holdings in the economy, four wealth quintiles and the wage premium. Calibration fit is presented on Table 2. Table 3 presents the calibrated parameters. Note that the model fits the target data with an error below 0.001, with the exception of the Q_{80} moment. This inability to match the upper tail of the wealth distribution is the result of a low level of capital-to-output required to achieve the target level of the wage premium. This is due to the fact that we use a measure of productive capital that excludes residential structures, a large portion of household wealth, to estimate the parameters of the production function. It also explains the low level of calibrated discount factors.

Table 2: Calibration fit

Data moment	Description	Source	Data Value	Model value
65-on/all	Average wealth of households 65 and over	US Census Bureau	1.51	1.51
w_{NR}/w_R	Wage Premium	CPS	0.00	0.00
$\overline{n}$	Fraction of hours worked	PWT	1/3	1/3
$Q_{20}, Q_{40}, Q_{60}, Q_{80}$	Wealth percentiles	WID	$-0.01, 0.00, -0.04, 0.17$	$-0.01, 0.00, -0.04, 0.30$

Table 3: Parameters Calibrated Endogenously

Parameter	Value	Description
φ	4.28	Bequest utility
$\beta_1, \beta_2, \beta_3, \beta_4$	0.939, 0.903, 0.902, 0.890	Discount factors
χ	6.1	Disutility of work
$\underline{h}$	0.02	Borrowing limit

6 Results

The main experiment conducted in this section is to calculate a new steady state where government and technology parameters are substituted to match more recent values. Concretely, we have chosen 2010 values to calibrate the new steady state. We then calculate the changes in observed inequality statistics and evaluate which parameters are responsible for the most significant changes in those variables. Note that the transition between steady states is not taken into account.

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_1, β_2, β_3, and β_4), the borrowing constraint ($\underline{h}$), depreciation (δ), and production function parameters (ϕ_1, ϕ_2, σ and ρ).

Table 4 displays a comparison between 1980 and the new steady state parameter values. The most relevant changes in the government calibration are in capital income taxes, the labor income tax progressivity parameter, the level of government debt and Social Security taxes. Investment prices are calibrated to match the observed drop from 1980 to 2010. Finally, group employment weights are adjusted to match those observed in 2010.

Results from the experiment are displayed on Table 5. Model pre- and post-tax Gini index increase by 0.053 and 0.050, respectively, when compared to the 1980 calibration of the U.S. economy, or 42 and 47% of the total increase observed in the data between 1980 and 2010. The gap between the two inequality statistics also increases but only by

Table 4: Parameter shifts

Parameter	Description	1980	New SS
τ_c	Consumption tax	0.050	0.054
τ_k	Capital income tax	0.469	0.360
θ_1	Tax level parameter	0.850	0.869
θ_2	Tax progressivity parameter	0.160	0.095
B/Y	Government debt	0.320	0.880
τ_{ss}	Employee SS tax	0.061	0.077
$\tilde{\tau}_{ss}$	Employer SS tax	0.061	0.077
ξ	Investment price	1.000	0.586
p_1	NRS weight	0.226	0.392
p_2	NRU weight	0.170	0.134
p_3	RS weight	0.181	0.228

a fraction of the observed data. The wealth Gini index also increases but only by 0.05, compared to the 0.07 change observed in the data. The non-routine wage premium in the new steady state is nearly one and a half times larger than the one actually observed in the data, indicating that the increase in the Gini index is being driven by an excessive increase in this statistic compared to the one observed in the data.

To counter this drawback we calibrate a new steady state in which the drop in investment prices is such that the non-routine wage premium in 2010 is matched exactly. This implies a 30% drop in the relative price of investment in lieu of the 40% drop observed in the data. This steady state is characterized by a smaller increase in pre- and post-tax income dispersion.

Note that the inequality statistics generated by the model are significantly below their empirical counterparts. This is the result of limited sources of inequality built into the model. Within each of the groups, differences in income between individuals are the result of either age/experience or idiosyncratic risk. Differences in permanent ability as in Brinca et al. (2016), which capture residual inequality within each group, are not modeled. Nevertheless, we are focused on changes rather than levels at this stage.

We run additional experiments to isolate the contribution of each set of parameters. Figure 3 provides a visualization of the results, which are detailed on Table 5. The parameter which contributes the most to the pre-tax income Gini is the change in the

Table 5: Experiment Results

	Data		Model									
	1980	2010	1980	New SS	New SS*	$\tilde{\tau}_{SS}, \tau_{SS}$	τ_k	θ_2	B/Y	Employment	ξ	ξ^*
Labor share	0.636	0.564	0.643	0.574	0.578	0.644	0.637	0.641	0.647	0.629	0.623	0.630
Gini index (pre-tax)	0.458	0.586	0.315	0.369	0.346	0.294	0.322	0.322	0.308	0.308	0.371	0.354
Gini index (post-tax)	0.374	0.480	0.229	0.279	0.265	0.206	0.233	0.246	0.230	0.224	0.252	0.245
Gini gap	0.085	0.107	0.086	0.090	0.082	0.088	0.089	0.076	0.079	0.085	0.119	0.109
NR wage premium (%)	0.000	0.143	0.000	0.334	0.143	-0.025	0.084	0.012	-0.060	-0.161	0.375	0.217
Wealth Gini index	0.81	0.88	0.70	0.73	0.72	0.70	0.69	0.69	0.69	0.69	0.74	0.72
Q_{20}	-0.01	-0.03	-0.01	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
Q_{40}	0.00	-0.03	0.01	0.01	0.01	-0.01	0.00	0.00	0.00	-0.01	0.01	0.00
Q_{60}	0.04	0.00	0.05	0.07	0.08	0.05	0.06	0.07	0.06	0.06	0.07	0.07
Q_{80}	0.17	0.12	0.31	0.22	0.23	0.31	0.31	0.32	0.32	0.32	0.21	0.23

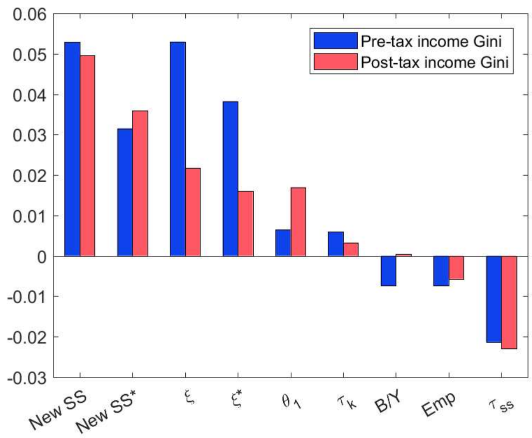
Notes: table indicates the values of each statistic from the data and the different model calibrations. A star indicates the model where the drop in the relative price of investment is set to match the rise in the non-routine wage premium. The isolated impacts of τ_c, θ_0 and government spending are not shown due to their residual contribution to the changes of the statistics of interest.

relative price of investment. This is due to its significant impact on the non-routine wage premium, which creates a large wedge between non-routine and routine wages. However, the impact of this parameter is dampened by the progressivity of the labor tax schedule (which is kept at 1980 levels), with the increase of the post-tax income Gini being limited to almost half of the pre-tax increase.[7] By itself, the change in investment prices is responsible for 21% of the increase in the pos-tax Gini index. In the experiment where the non-routine wage premium is matched, this figure drops to 15%.

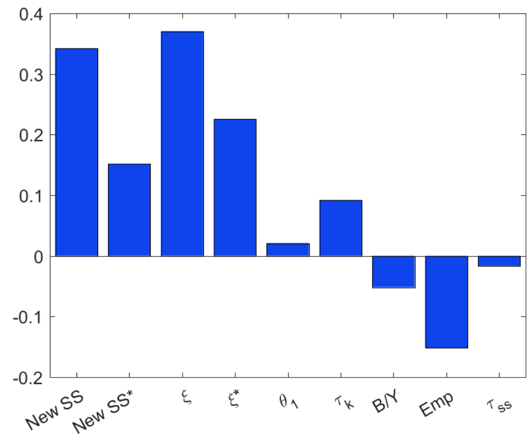
The drop in progressivity also increases income dispersion by reducing the distortion on the labor supply at the top of the earnings distribution. In particular, it has a significant impact on the pos-tax inequality. Coupled with the drop in investment prices, it is responsible for generating the large increase in the post-tax income Gini in the full model. Alone, this channel accounts for 16% of the change in the post-tax Gini observed in the data.

The reduction in capital income taxes fosters capital accumulation, increasing the marginal productivity of non-routine labor relative to routine labor and raising the wage

[7] Note that changes in the non-routine wage premium have a non-trivial effect on the earnings distribution: while they increase the wage of the non-routine skilled group, it also reduces the negative differential of non-routine unskilled workers, bringing their earnings closer to the average.



(a) Income dispersion



(b) Change in wage premium

Figure 3: Impact of changes in parameters. A star indicates the model where the drop in the relative price of investment is set to match the rise in the non-routine wage premium. The y-axis indicates the difference observed in each calibration with respect to the 1980 calibration.

premium. Furthermore, it also produces greater post-tax capital income, contributing to the increase in income dispersion, albeit only modestly.

Some of the observed structural shifts during our period of analysis have also contributed to a dampening in the effects produced by investment-specific technological change and the reduction in progressivity. The large increase in government debt-to-GDP produces a crowding out of private capital, reducing the relative productivity of non-routine labor and the wage premium. The employment shifts in this period, in particular the surge in the relative employment of non-routine workers, has also counteracted wage premium growth in a significant manner, generating a modest reduction in overall income inequality by itself.

Finally, the increase in Social Security contributions has a large negative effect income dispersion. This is the result of the highly progressive nature of the Social Security bloc in the model: contributions are collected as a flat tax on labor income and redistributed lump sum to retirees.[8] This apparent modeling limitation cushions the increase in income inequality from other sources, implying that the increase in the income Gini in the

[8]Both the data and the model pre-tax income Gini include pensions, but exclude Social Security contributions.

full model would be larger if the impact of social security distributions would be more muted.

Our future work will involve the nesting of a total of four labor varieties in the production function, which will allow us to generate an endogenous skill premium and increase the quantitative significance of the changes in the income Gini index.

7 Conclusion and Future Work

We propose a framework which can quantitatively explain the rise in inequality in the U.S. since 1980. Our calculations show that structural changes in technology, government policy and employment are able to produce an increase of the income Gini index which is one third of the change in post-tax income Gini observed in the data.

The main mechanisms at play are the rise in the non-routine wage premium, which increases the dispersion in the earnings distribution and the ability of a fraction of the population to accumulate greater amounts of wealth relative to the lower quintiles. Additionally, the reduction in the progressivity of the labor income tax schedule reduces labor supply distortions and increases the post-tax income Gini index. We show that ISTC alone accounts for 15% of the change in observed post-tax income Gini, while the reduction in progressivity accounts for 16%.

Our next steps involve expanding the model to account for the role of capital-skill complementarity, in the same manner that capital-non-routine complementarity was introduced. This will allow us to study the effects of technological change on both the non-routine and the skill wage premium in a single framework, and attempt to observe the impact of these two theories of the impact of technological change on earnings inequality. We will also refine our experiment by recasting it as unexpected change in the trend of ISTC, enabling us to analyze the path of income dispersion measures in a more realistic way relative to the comparison of steady states.

A Wage premium regression

The following cross-sectional regression model is estimated separately for each gender and year t, weighted by ASEC weights:

$$\ln w_{i,t} = \alpha_0, t + \alpha_{1,t} X_{i,t} + \epsilon_{i,t} \quad \text{for } t \in \{1967, ..., 2016\}$$

The dependent variable is the log of weekly wages, obtained by dividing the yearly labor earnings by the number of weeks worked. The categories contained in $X_{i,t}$ are:

1. **Five education categories**: high school dropouts, high school graduates, some college, college graduate, and greater than college;
2. **Two task types**: routine and non-routine;
3. **Three race types**: white, black, and non-white other;
4. **Potential experience**: 5, 15, 25, 35, 45 years.

We use white college males with 45 years of experience and in routine occupations as the base set of categories. The wage premia are obtained as the difference between the average log-wages in each year for two groups whose only difference is in either skill or task type.

B Production function

Given the fact that $Y_t = w_t^{NR} N_t^{NR} + w_t^R N_t^R + r_t R_t$, we can write income shares as:

$$s_{N,t} = \frac{w_t^{NR} N_t^{NR} + w_t^R N_t^R}{Y_t}, \tag{27}$$

$$s_{K,t} = \frac{r_t K_t}{Y_t}, \tag{28}$$

where $s_{N,t}$, $s_{K,t}$ are the shares of labor and capital, and $s_{N,t} + s_{K,t} = 1$. Firm optimality conditions together with equations 27 and 28 imply the following relationships between factor shares and quantities:

$$\ln\left(\frac{s_{K,t}}{s_{NR,t}}\right) = \ln\left(\frac{\phi_2}{1-\phi_2}\right) + \left(\frac{\rho-1}{\rho}\right)\ln\left(\frac{K_t}{N_t^{NR}}\right), \tag{29}$$

$$\ln\left(\frac{s_{R,t}}{s_{Z,t}}\right) = \ln\left(\frac{\phi_1}{1-\phi_1}\right) + \left(\frac{\sigma-1}{\sigma}\right)\ln\left(\frac{N_t^R}{Z_t}\right), \tag{30}$$

where $s_{NR,t}$, $s_{R,t}$ and $s_{Z,t}$ are the income shares of non-routine labor, routine labor, and the composite input. We calibrate ϕ_1, ϕ_2, ρ, and σ by estimating 29 and 30 using the following two-step procedure: (i) estimate 29 by OLS and compute implied quantities for Z_t; (ii) estimate 30 by OLS, using the estimates for Z_t.

For the labor shares, we use the series presented on Section 3 and rescale them to match the BLS private non-farm labor share. The capital labor share is calculated as the residual of the (BLS) labor share and the the profit share from equation. The share of the composite Z_t is the sum of the capital and non-routine income shares.

Because the goal is to obtain a measurement of inputs in similar units, we measure input quantities in dollars and deflate them with the GDP price deflator (2005=1). For labor inputs we use the series of aggregate wage bills by task type rescaled so as the sum of the labor shares of both groups matches the BLS aggregate labor share. Thus, changes in wage bills reflect either changing hours or changing productivity. For this reason, the non-routine aggregate wage bill is rescaled so that the level of the wage premium does not affect our measurement of the non-routine input. The quantity of capital is measured as the stock of private and government non-residential capital.

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