Ana Ferreira
Nova School of Business and Economics
m.ferreira@novasbe.pt
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Skill-Biased Technological Change and Inequality in the U.S.

Progresso Tecnológico Enviesado em Função das Qualificações e Desigualdade nos E.U.A.

Ana Ferreira

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ABSTRACT
Since the 1980s, income inequality has increased markedly and has reached the highest level ever since it started being recorded in the U.S. This paper uses an overlapping generations model with incomplete markets that allows for household heterogeneity that is calibrated to match the U.S. economy with the purpose to study how skill-biased technological change (SBTC) and changes in taxation quantitatively account for the increase in inequality from 1980 to 2010. We find that SBTC and taxation decrease account for 48% of the total increase in the income Gini coefficient. In particular, we conclude that SBTC alone accounted for 42% of the overall increase in income inequality, while changes in the progressivity of the income tax schedule alone accounted for 5.7%.
Keywords: Technical change; income inequality; wealth inequality; heterogeneity; taxation.

JEL Classification: E21; J10.

RESUMO
Desde a década de 1980, a desigualdade de rendimento aumentou acentuadamente e está no nível mais alto desde que foi iniciado o seu registo nos EUA. Este artigo usa um modelo de gerações sobrepostas com mercados incompletos que permite a heterogeneidade do agregado familiar. O modelo é calibrado para a economia dos EUA e tem como objetivo estudar como o *Skill-Biased Technological Change* (SBTC)) e as mudanças na tributação explicam quantitativamente o aumento da desigualdade entre 1980 e 2010. Estima-se que o SBTC e a redução da tributação respondem por 48% do aumento total do coeficiente de Gini. Em particular, concluímos que o SBTC sozinho foi responsável por 42% do aumento geral na desigualdade de rendimento, enquanto as mudanças na progressividade do imposto sobre o rendimento por si só foram responsáveis por 5,7%.
Palavras-chave: Progresso tecnológico; desigualdade de rendimento; desigualdade de riqueza; heterogeneidade; impostos.

1. Introduction

Some argue that we are in the period of a "Forth Industrial Revolution", which moved production function shares. There is an increasing concern in the possible dominance of technology over the human labor: "Automation and AI will lift productivity and economic growth, but millions of people worldwide may need to switch occupations or upgrade skills" (Manyika et al. 2017).

Most of the literature focus on the substitution of low-skilled labor for capital (Autor, Levy, and Murnane 2003; Acemoglu and Restrepo 2018). Although, it is essential to have in mind that high-skilled automation can, and will probably be an issue due to artificial intelligence and machine learning. Acemoglu and Restrepo (2016) describe: "If the long-run rental rate of capital relative to the wage is sufficiently low, the long-run equilibrium involves automation of all tasks".

Hence, as shown by Acemoglu and Restrepo (2018), low skill-automation will increase wage inequality because people are being substituted by machines or losing their job. A social measure to reduce inequality is using taxation. (Saez 2001), claimed that labor tax rates should be U-shaped, separating households with low and higher income distributions, instead of the previous proposed lump-sum taxation (Mirrlees 1971). Furthermore, Aiyagari (1995) ensures that with incomplete markets and uncertainty, optimal capital taxation is positive.

In this manner, the present article pretends to answer *quantitatively* how SBTC and taxation changes account for the paths of income inequality in the U.S from 1980 to 2010. Our contribution is similar to Krusell et al. (2000). The authors show that capital-skill complementary changes account for most of the variations on the skill premium. Other related studies also measure wage inequality through skill premium (Heckman, Lochner, and Taber 1998). We apart from this specification and take into account income and wealth distributions that the authors abstract from. Furthermore, we use income inequality instead of skill premium to account for the changes in wages.

The model developed in this framework is an overlapping generations model with an incomplete markets and an uninsurable idiosyncratic risk that allows skill-biased technological change, which is modeled assuming that agents have different abilities. Thus, households born with different abilities, which are complemented or substitutable by capital. Households can face ex-ante heterogeneity, or they can suffer a posterior income shock, which creates ex-post heterogeneity. Furthermore, taxation plays a crucial role in this model, since labor taxes can distort labor supply (Golosov, Troshkin, and Tsyvinski 2016) and affect the household's skill investment (Heathcote, Storesletten, and Violante 2017). We use a non-linear labor tax function developed by Bénabou (2002), to define the level and the progressivity of the tax schedule.

Our model reproduces simultaneously some phenomenon of the U.S. economy from 1980 to 2010, namely: the skill premium rise; a growth in income and wealth inequality; a rise in skilled labor share, and a reduction on the unskilled labor share. We were able to account for 48% of the total change in income inequality. In particular, we show that SBTC alone account for 42%, while taxation alone accounted for 5,7%.

The rest of the work is organized as follows. In Section 2 we discuss some related literature and empirical facts. In Section 3, we present the model and the calibration method and in Section 4 the results. Section 5, concludes the work.

2. Related Literature and Facts

It is quite a consensus that labor share has been declining since 1980 (Eden and Gaggl 2018; Karabarbounis and Neiman 2013). Some recent models attribute the labor share contraction to the substitutability between capital and unskilled labor in the technological production function. This substitution in the course of investment-specific technological change (ISTC) has been referred as automation.

Particularly, Eden and Gaggl (2018) calibrate an aggregate production function that highlights the interaction between information and communication technology (ICT) and different types of labor for the U.S. economy and find that the decline in the aggregate labor share is explained by the decrease in routine occupations, since the income share of non-routine labor has been rising.[1]

For instance, automation can create distinct effects on the economy. On the one hand, it can increase the aggregate welfare, because it pushes up productivity and, as a result, the factor prices change (Acemoglu and Restrepo 2018; Eden and Gaggl 2018)[2]. But on the other hand, as capital becomes cheaper, or in other words, as investment prices decline, unemployment rates will increase due to a shift in companies' factor demand, which will raise the demand for skilled people and lower the demand for unskilled people (Acemoglu and Restrepo 2016). As demand-supply rule takes place, unskilled households will see their wages decrease, although skilled agents will face an increase in their salaries.

In fact, U.S. wage structure shows that since 1970 there is an increase in dispersion in household earnings, especially in different levels of education, age, and experience. Furthermore, Katz et al. (1999) mentioned that the observed wage structure for U.S. seems to translate an increase in inequality. The author summarises several reasons that are attributed to wage inequality: (i) higher demand for more educated people driven by SBTC; (ii) loss in the wage premium paid to less educated people, due to a rising globalisation pressure; (iii) higher dispersion in skills, due to increase of unskilled immigration; (iv) and changes in wage setting norms.

As a consequence, households will pursue different behaviors when they face income risk. Agents can create an ex-ante response, i.e., in anticipation of the shock they tend to increase their precautionary savings and engage in contracts in which wages are kept constant (Krueger, Mitman and Perri 2016). However, agents can act after they face a shock, i.e., an

[1] It is very important to distinguish between occupation and worker skill type. Some professions are non-routine, although they do not infer a skilled household, i.e., an educated household, for example, an electrician does not have a college degree, although performs a non-routine job. Contrary, diagnosis doctors are skilled, but they perform a routine occupation. Most of the routine occupations are conducted by agents that have a college degree or higher.

[2] Indeed, Krusell et al. (2000) concludes that the increase in inequality occurs jointly with the reduction of the investment prices and recently (Eden and Gaggl 2018) shows that the value of information and communication technology falls considerably after 1982.

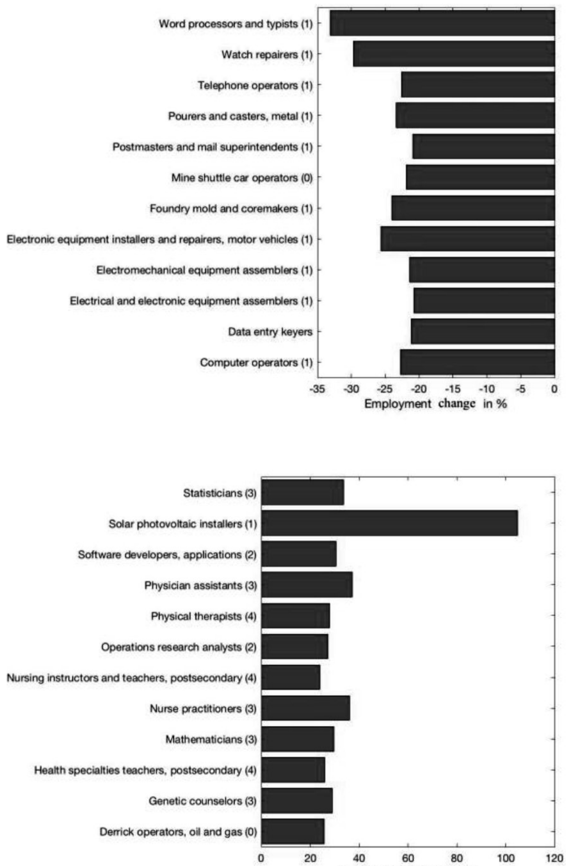
ex-post response to risk. In this case, households will make a consumption revision, which will be lower if the income shock is negative, or higher otherwise (Heathcote, Storesletten and Violante 2014). To smooth the shocks, households can change their skills, this is, they can increase their human capital, becoming skilled (Heathcote, Storesletten and Violante 2017).

The U.S. wage pattern is related to technological development because periods of significant technological developments are correlated with high skill premiums. Indeed, SBTC increased the demand for skilled workers since 1980, and this increase explains part of the rise in education wage premium. Furthermore, the more demanded occupations in 2026 will be those that are less likely to be automated and will be more related to social skills, creative thinking, and problem-solving capacities. These non-routine occupations are related primarily with high-skilled jobs which need higher levels of education and have more significant earnings.

Figure 2 presents a projection for the growing job positions for 2026, which shows that to have access to most of them it is necessary to incorporate in distinct levels of education. In reality, most of those occupations will require college degrees.

These recent projections support (Heckman, Lochner, and Taber 1998) who introduce human capital accumulation in an OLG model in order to explain the rise in the wage inequality, measured by the skill premium, without giving a unique role to capital, and conclude that the higher demand for high skilled labor induces a supply response, thus more and more people will go to college as a response to the required features.

Figure 1: Occupations change for 2026



Note: The chart on the left presents the less demand jobs, and the right figure shows the most demand jobs, where 0 indicates that there is no need for formal education credential; 1 indicates that it is necessary a high school diploma; 2 indicates that it is necessary a Bachelor's degree; 3 for Master's degree; and 4 for Doctoral and advanced degree. Source: U.S. Bureau of Labor Statistics.

The skill premium can be seen as an explanatory variable for the decreasing labor share in the course of SBTC. Murphy and Welch (1992) calculated that the skill premium grows 3,3% each year, ceteris paribus. Furthermore, Krusell et al. (2000) show that there was a decline in 1970 in the skill premium, but in 1980 there was a severe increase. Figure 3 is the representation for the skill premium since 1980 for the U.S. economy, which shows that there is, indeed, an increase that was maintained until 2010, although since then it has been quite steady. The more considerable difference is coming from the college skill premium, calculated as the ratio for bachelor degrees and high school degrees. This problematic of income polarization may continue to increase due to the higher demand for high-wage occupations that can grow more than middle-wage jobs.

As this trend continues, the problem can appear because not everyone has the same opportunity to access to higher education. Thus, inequality surges, because automation leads to unemployment in low-skilled people ((Acemoglu and Restrepo 2018)) and because wealthier agents tend to be more educated and older (Krueger, Mitman, and Perri 2016).

Figure 4 compares the Gini Index for pre-tax and post-tax income and shows that inequality is rising since 1980. Thus, although taxes are taking influence in reducing inequality, it seems that this has not been entirely effective. Indeed, the income share of the bottom 90% is dropping in the same period. Of course, distinct levels of income correspond to different levels of experience, skills, and productivities, as it will be clarified in section 3.

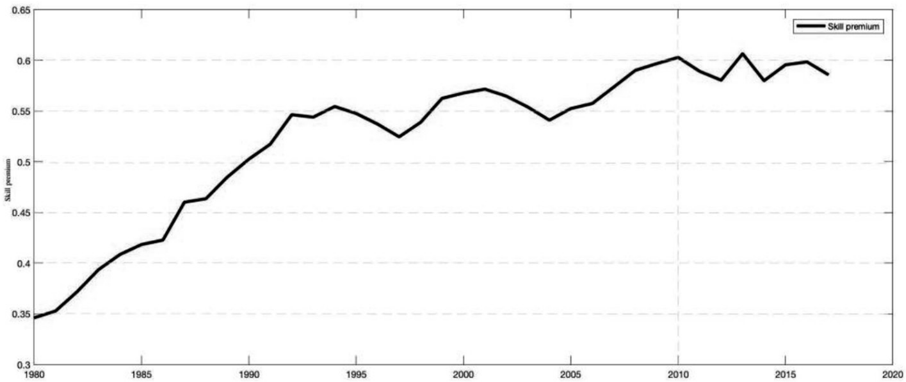
Taxation can be a force to increase output and consumption because it affects government spending (Ferriere and Navarro 2018). The Mirrlessian approach concludes that individuals with highest skills have optimal taxation of zero (Diamond 1998). However, recent studies show that there are welfare gains when we move to a non-linear tax function especially when the government does not observe the skills of the citizens (Gorry and Oberfield 2012). Thus, the government should set different taxation on workers with different abilities and, in consequence, with different elasticities towards capital. Heathcote, Perri, and Violante (2010) find that the optimal income taxation structure to maximize social welfare is only a two-parameter function, that embraces the level of taxation and the progressivity of tax, as it will be clarified in section 3. Using this, and also, other income taxation approaches, Guner, Kaygusuz, and Ventura (2014) find that it is possible to reduce the Gini Index from 0,56 to 0,55 only by using labor taxation.

Although this is a useful measure to reduce income inequality, taxation can create an adverse effect. As the government increases progressive taxation, agents have less incentive to work, and they prefer to invest less in skills, which can create even more heterogeneity ((Stiglitz 1982)).

Progressive taxation is essential to redistribute after-tax income across ex-ante heterogeneous households. Thus an optimal policy can create beneficial effects on society. (Krueger, Ludwig, and others 2013) found optimal labor taxation of 34,1% taking into account skilled and unskilled households and, concluded that this taxation leads to a lower Gini index, higher GDP and consumption, and more people deciding to go to college.

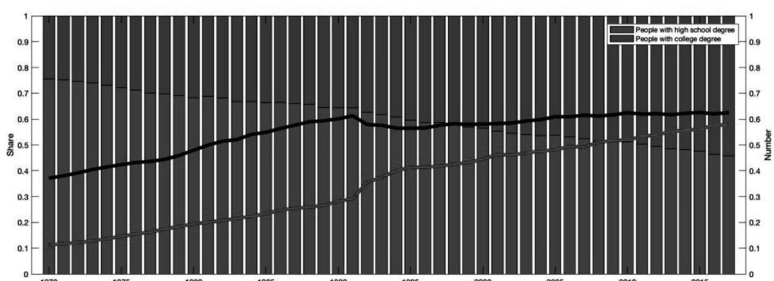
Figure 6 shows the results for labor tax progressivity in the U.S. since 1946 using the methodology of (Ferriere and Navarro 2018). The average progressivity tax is 11,9% (s.e. 0,029) between 1980 and 2010. In the 80's progressive tax rate achieved its maximum, however since the 90's the progressivity tax has been established close to 10%, resulting in a decrease comparing 1980 with 2010.

Figure 2: Log Skill Premium



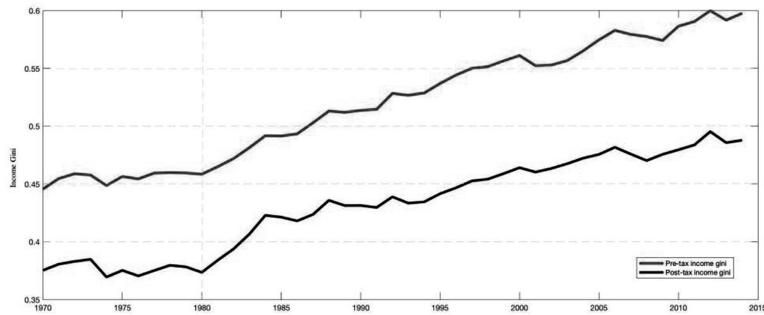
Note: Calculated as the ratio between skill and unskilled wages. Skilled wages are considered for those who have a bachelor degree, or higher and unskilled wages are those coming from a high-school degree. Own calculation. Data source: Bureau of Labor Statistics.

Figure 3: Number of people with higher education background



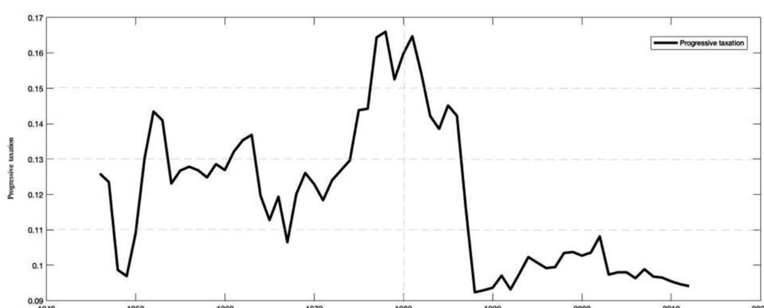
Note: Division of people that completed High school and College with 25 years and over, the lines are the number of people that completed these degrees divided by 1 x 10^8. Data source: Census Bureau.

Figure 4: Inequality



Source: World Inequality Database (WID).

Figure 5: Progressive Taxation



Note: Own calculation following the method of Ferriere and Navarro (2018). More details on annexes.

3. Model and Calibration

This paper uses the model 2 as outlined in the introduction chapter. The model is calibrated to match the U.S. economy in 1980, in light with the method used by (Brinca et al. 2016) and (Brinca et al. 2018). Preferences and age profile of wages, ρ_u and σ_ϵ are setting according to (Brinca et al. 2016). The first discount factor is set to match the capital-output ratio in 1980 and the second discount factor is set to match the income share of the bottom 90%.

The distribution parameters, Φ_1 and Φ_2 are fixed to 0,55 and 0,8, respectively, so that the skill premium and the quantities of labor supplied are close to levels observed in 1980 (Eden and Gaggl 2018). Furthermore, the elasticity of substitution between capital and skilled labor is 0,43, and the elasticity of substitution between capital and unskilled labor is 2,33.

The disutility of work, χ, and the variance of ability, σ_a, are set using the Simulated Method of Moments (SMM). Furthermore, risk aversion was set to 1,2. We, also assume that capital depreciates at 0,06 and the share of non-routine skills is set to 40%.

Wages

The wage profile through life-cycle is calibrated directly from the data. We run equation (1) illustrated below using data from Luxembourg Income and Wealth Study (LWS).

$$\ln(w_i) = \ln(w) + y_1 j + y_2 j^2 + y_3 j^3 + \epsilon_i$$

where j is the age of individual i. To calculate ρ_u and σ_ϵ we use PSID data and regressed the wage equation, then we use the residuals in order to estimate both parameters. These parameters are kept constant across steady-states.[3]

Preferences

There has been an extensive debate in the literature relative to the value of Frisch elasticity of labor supply, η. The estimates for are comprehended between 0,5 to 2.[4] We set the Frisch elasticity to 1 as Trabandt and Uhlig (2011), to ensure that the labor supply is not affected by technological shocks.

Taxation

We use the labour income tax function, to capture the progressively of both the tax schedule and government transfers. In order to estimate θ_1 and θ_2 we follow the method of (Ferriere and Navarro 2018). Thus we fix $\theta_1 = 0{,}85$ and $\theta_2 = 0{,}16$, for 1980. For 2010 the values of θ_1 and θ_2 are set to 0,87 and 0,095, respectively.

The rates for social security are set assuming no progressivity, the taxes on behalf for employer and employee are set to 7,65% for both steady states. Furthermore, capital taxation and consumption taxation are set according to the values obtained by (Mendoza, Razin, and Tesar 1994), which are $\tau_c = 5{,}4\%$ and $\tau_k = 46{,}9\%$. For 2010 these values are 5,5% and 36% for consumption and capital, respectively, following Brinca et al. (2016).

[3] The values are: $y_1 = 0{,}2647$; $y_2 = -0{,}00539$ and $y_3 = -0{,}000036$; $\rho_u = 0{,}335$; $\sigma_\epsilon = 0{,}3066$.

[4] For a more detailed view see Reichling and Whalen (2012).

Endogenous calibrated parameters

Since some parameters do not have an empirical counterpart, they are calibrated using SMM. These parameters are calibrated to match the target values in Brinca et al. (2016), as in Table 1. We choose β_1, β_2, χ, σ_a and φ to minimize the loss function:

$$L(\beta_1, \beta_2, \chi, \sigma_a, \varphi) = || M_m - M_d ||$$

M_m is the moment in the data and M_d refers the moments in the model. We have five instruments, and five moments in the data to have an identified system. Table 2 displays the values of the parameters calibrated by SMM.

Table 1: Calibration fit

Data moment	Description	Source	Target	Model value
$\frac{K}{Y}$	Capital-to-output ratio	PWT 8.0	3,3	3,3
B90	Income share of the bottom 90%	WID	0,3287	0,33
$\bar{n}$	Fraction of hours worked	OECD	0,3	0,3
IGini	Income Gini	WID	0,485	0,46
$Q_{75\text{-}80}/all$	Av wealth of 75-80/Av wealth of all	LWS	1,513	1,51

Table 2: Parameters calibrated using SMM

Parameter	Values	Description	Target
β_1	0,27	Beta 1	$\frac{K}{Y}$
β_2	1,0043	Beta 2	Income share of the bottom 90%
χ	8,3	Disutility of work	Fraction of hours worked
σ_a	0,15	Variance of ability	Income Gini
φ	13,43	Bequest motive	Av wealth of 75-80/Av wealth of all

4. Results and Discussion

The supply of skills is shaped by many variables, such as demographic trends, preferences and education shifts. Due to technological changes, workers may want to upgrade their skills, as the skill demand increases. Initially, technical change was viewed as factor-neutral, this is, improvements in the TFP leave marginal rates unchanged. However, empirically, we observe a rise in the skill premium, as well as the increase in skilled labor supply, as we show in section 2. Even with a higher supply of skilled people since 1970, wages for skilled people kept rising, which can be observed as pieces of evidence of skill-biased technological change. In fact, Acemoglu and Autor (2011) argue that technical changes are by its nature skill-biased.

Thus, some argue that the changes in production are not just an effect of the decrease in the price of investment, but also an increase in the skill supply. As society keeps getting more educated, employers will prefer to use people's ability to make them even more productive and, as they gain experience they can be more profitable more rapidly than unskilled households. Furthermore, skilled households have an advantage compared with unskilled households, since they give less uncertainty to the employer.

For simplicity, most of the studies assume that production function elasticity of substitution between capital and labor is equal to 1. However, recently, a departure from this assumption has taken place. If the elasticity of substitution between capital and unskilled labor is higher than 1, firms will substitute labor for capital. In this manner, we guarantee that the growth of skilled labor is greater than the growth of unskilled labor. In this sense, if $\sigma > 1$, then the two inputs are substitutes. Thus, the economy will be endogenously augmented through capital, because an increase in A_{kt} will increase the marginal productivity of capital. This effect occurs jointly with an increase in the skill premium and marginal productivity of skilled labor. However, the unskilled labor has lower productivity. Contrary, if the elasticity of substitution between capital and unskilled labor is lower than 1, the two factors will be complements and the demand shift will decrease the skill premium, and thus, the factors are complements. This goes according with the results reported by Acemoglu and Autor (2011), Autor, Levy, and Murnane (2003), Karabarbounis and Neiman (2013) and Krusell et al. (2000).

Krusell et al. (2000) show that the values for the elasticity of substitution between skilled labor and capital are between 0 and 1,2 and the values for the elasticity of substitution between unskilled labor and capital are between 0,5 and 3. Therefore, skilled labor and capital tend to be complements and unskilled labor and capital tend to be substitutes. This interpretation has consequences for taxation because taxes depend on the heterogeneous characteristics of the households. Hence agents with higher skill level should face higher taxes and unskilled households should face lower taxes, that is, the lower the substitution between factors the higher should be the tax rate imposed, and vice-versa.

To capture the SBTC, we use capital-augmenting technology, A_{kt}, as a substitute. We use an elasticity of substitution for skilled labor and capital lower than 1. Thus these factors are gross complements. Contrary, we set an elasticity of substitution for unskilled labor and capital higher than 1, stating that these factors are gross substitutes.

Our experiments are as follows. First, we calibrated the model for the U.S. to match the capital-output ratio, average hours, and moments of income and wealth distributions for 1980. Then, we changed the tax system according to 2010 values, as referred in section 3.

After this change, we compute the changes in the total factor productivity (TFP) and skill-biased technological change to replicate the growth in PIB per capita between 1980 and 2010. We follow (Greenwood, Hercowitz, and Krusell 1997) and keep the contribution the TFP and SBTC constant and equal to one-half.[5]

With this model, we capture several aspects of the U.S. economy since 1980 to 2010, such as: (i) rising skill premium; (ii) increase in income and wealth Gini coefficient; (iii) decrease in the wealth share owned by the bottom 90% of families (iv) an increase in skilled labor share; (v) a reduction in unskilled labor share; (vi) and, an increase in wage dispersion. Furthermore, our model recognises, as expected, that people spend more hours working and the supply of skilled households increased in 2010, due to a decrease in progressive labor taxation.

Our model accounts for 48% of the total increase in the income Gini Index for the period. Then, we access the contribution of changes in the tax system and changes in the investment-specific technological change separately, by changing each factor at a time. We find that changes in the tax system account for 5,7% of the total increase in income inequality, while changes in investment-specific technological change account for 42%.

5. **Conclusion**

Most of the economists believe that the U.S. wage structure is influenced predominantly for technological shifts, especially since 1980. We use an overlapping generations model with incomplete markets, featuring skill-biased technological change to answer *quantitatively* how skilled-biased technological change and taxation explain income inequality in the U.S. from 1980 to 2010. To generate SBTC we assume that agents born with different abilities, whereby some are endowed with abilities that are complemented by capital and others are endowed with capabilities that are substituted by capital, i.e., we use the substitution of unskilled labor for capital as a reasonable mechanism to explain the skill-biased technological change ((Karabarbounis and Neiman 2013; Krusell et al. 2000)).

We calibrated our model to match the U.S. economy in 1980. The model captures the rise in the skill premium, the increase in income inequality, as well as the increase in the share of the skilled population, opposing to the decrease in the share of unskilled labor. This shows that high-skilled workers have, indeed, an advantage in the labor market because they give less uncertainty to the employers. More importantly, we find that changes in taxation and capital-skill complementary jointly account for 48% of the increase in income Gini. Furthermore, we find that SBTC account for 42%, while taxation alone accounted for 5,7%.

An essential introduction to the model can pass for add an endogenous education choice in light with (Ábrahám 2008). Before entering in the economy, a household can observe its ability and decide whether to begin to work as an unskilled worker or to attend college. This decision will depend not only on the distribution of agents ability, but also on the initial wealth distribution, taking into account a costly educational choice. Moreover, it is also possible to study an optimal taxation across the transition path between steady-states.

[5] With this approach the authors conclude that the growth in output is mostly explained by investment-specific technological change.

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Appendix

Tax function

Given the tax function[6]

$$ya = \theta_1 y^{1-\theta_2}$$

which we employ, the average tax rate is defined as

$$ya = (1 - \tau(y))y$$

thus

$$\theta_1 y^{1-\theta_2} = (1 - \tau(y))y$$

$$1 - \tau(y) = \theta_1 y^{1-\theta_2}$$

$$\tau(y) = 1 - \theta_1 y^{1-\theta_2}$$

$$T(y) = \tau(y)y = y - \theta_1 y^{1-\theta 2}$$

$$T'(y) = 1 - (1 - \theta_2)\theta_1 y^{-\theta 2}$$

In this sense, the tax wedge for any two incomes (y_1, y_2) is given by

$$1 - \frac{1 - \tau(y_2)}{1 - \tau(y_1)} = 1 - \left(\frac{y_2}{y_1}\right)^{-\theta_2}$$

and therefore independent of the scaling parameter θ_1. In this manner, one can raise average taxes by lowering θ_1 and not the progressivity of the tax code, since the progressivity is uniquely determined by the parameter θ_2.

Labor tax function calculation

In order to estimate θ_1 and θ_2 we follow (Ferriere and Navarro 2014). The authors calculated the progressive tax rate as:

$$\theta_2 = \frac{AMTR - ATR}{1 - ATR}$$

[6] This first part of the appendix is borrowed from (Holter, Krueger, and Stepanchuk 2019).

We use data from (Mertens and Montiel Olea 2018) for AMTR (Annual Marginal Tax Rate). ATR (Annual Tax Rate) is equal to:

$$ATR = \frac{TotalTaxLiability}{TotalIncome}$$

The data for Total Tax Liability is retrieved from Statistic of Income and Total Income data is retrieved from (Piketty and Saez 2003).

Noticing that AMTR is equal to the sum of AMIITR (Average Marginal Individual Income Tax Rate) and AMPTR (Average Marginal Payroll Tax Rate), the formula was changed using only AMIITR, which incorporates solely tax rate series for the federal individual income tax, because the presented model already incorporates the taxation for social security.

The level of tax rate can be seen as a quantitatively close measure of the average tax rate (Ferriere and Navarro 2014). Thus, if we use $y = 1$ we are assuming that the household income equals to the mean income and we obtained the same values for both measures.

Table 3: Tax function estimations

Year	θ_1	θ_2	θ_2 with AMTR
1980	0,849	0,159	0,354
2010	0,869	0,095	0,214

Table 4: Parameters held constant across steady states

Parameter	Value	Description	Source
Technology			
α	0,36	Capital share to output	Literature
δ	0,06	Capital depreciation rate	Literature
ρ_u, σ_ϵ	0,335, 0,3066	$u' = \rho_u u + \in, \in \sim N\left(0, \sigma_\in^2\right)$	PSID
Preferences			
η	1	Inverse Frisch Elasticity	(Trabandt and Uhlig 2011)
σ	1,2	Risk aversion	Literature
Taxation			
$\tilde{\tau}_{ss}$, τ_{ss}	7,65%	Social security taxes	-

Table 5: Parameters change across steady states

Parameter	Description	1980	2010
Taxation			
τ_k	Capital tax	0,469	0,36
τ_c	Consumption tax	0,054	0,05
Φ_1	Level of labor tax	0,849	0,869
Φ_2	Progressivity of labor tax	0,159	0,095

Note: For capital and consumption taxation in 1980 we use the values from (Mendoza, Razin, and Tesar 1994) and for 2010 we use the values from (Brinca et al. 2016). For labor taxes we use (Ferriere and Navarro 2014) method.

Table 6: Inequality measures

Parameter	1980	2010	Source
Inequality			
Income Gini	0,4585	0,586	WID
Wealth Gini	0,8085	0,8842	WID
Bottom 90%	0,3287	0,243	WID