Employed and Poor? Wages, Technological Innovations and Policy

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Working Paper

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December 2020

Abstract

I explore the effect of automation on worker's welfare in a general equilibrium model with two skill types, wage bargaining, and education. In my model, automation does not necessarily displace workers, instead, workers and automation can perform the same functions within a sector. To evaluate the impact of automation, I use data from European countries for model calibration and simulations. I demonstrate that the changes in capabilities and prices of automation affect employment and wages differently, and the effect depends on whether individuals adjust their education decisions. First, when education is not adjusted, my model shows that a decline in the price of automation increases the employment rate but lowers wages. Meanwhile, an expansion of automation capabilities could increase or decrease the employment rate, depending on the labor market institutions. Secondly, when education adjusts, I show that declining prices and expanding capabilities of automation increase both wages and employment rates. Finally, I find that between 2005 and 2016, advancement in automation, rather than institutional changes or a shift to services, accounts for a significant portion of changes in educational attainment, employment, and wage inequality.

*E-mail: mlovchikova@ucdavis.edu. I am grateful to Athanasios Geromichalos, Giovanni Peri, Andrés Carvajal, Alan Taylor, Brendan Price and Claudia Sahm for comments and advice on the paper. I also thank seminar participants at UC Davis Macro/ International Presentation series, SAMMF workshop for job candidates, the WEAI Annual Conference 2019 and the 2019 Midwest Economic Association Annual Conference for their comments. All errors remain my own. The results and conclusions are mine and not those of Eurostat, the European Commission or any of the national statistical authorities whose data have been used.

1 Introduction

In the recent decade, public attention has been focused on one characteristic of automation: an advancement of its capabilities or, in other words, how many functions automation can perform. For example, an improvement in visual and speech recognition capabilities leads to public anxiety about the future of employment in such occupations as customer representative or radiology technician (Perrault et al., 2019). Another characteristic of automation is the price or how costly it is for a firm to use automation. Recently, the price of automation has reversed its downward trend. If between 1980 and 2010, prices in Europe have been declining by 16% per decade on average, in the 2010-2017 period, prices grew +4.5% (Table C3).[1] It is not clear whether these two trends in automation characteristics could amplify or cancel out each other's effect on the labor market because they are usually studied independently of each other. In this paper, I investigate whether these two characteristics of automation have different effects on workers' welfare and education.

My paper contributes to the understanding of the impact automation has on the labor market and education decisions. Plenty of papers exist that emphasize a displacement effect of automation when it is introduced to a sector or highlighting the role of automation in the creation of new tasks and occupations (Acemoglu and Restrepo, 2017; Susskind, 2017; Brynjolfsson and McAfee, 2014; Autor and Salomons, 2017). However, only a few researchers have ventured to investigate how automation coexists with workers (Leduc and Liu, 2019; Arnoud, 2018). Building upon this approach, I take a step further and analyze the impact of two distinct characteristics of automation in the same model: the price of automation and its capabilities. I argue that the difference in labor market responses to changes in those characteristics could be significant and should be accounted for in policy responses.

Moreover, I add to the discussion of the interaction between automation and policy. There are two strands of literature that are looking at this interaction from two different perspectives. On the one hand, existing labor policies could facilitate automation adoption and exacerbate its impact on the labor markets (Hornstein et al., 2007; Alesina et al., 2018). On the other hand, some researchers advocate using tax and labor market policies to mitigate the negative effects of automation (Guerreiro et al., 2017; Furman and Seamans, 2018). Some policies that are discussed as a potential response to automation, for example, unemployment benefits or universal basic income, have been studied independently from the automation (Marinescu, 2016, 2009). I evaluate the effectiveness of several policies - job protection, union support,

[1] I use relative investment prices from Penn World Tables as a proxy for automation prices (Feenstra et al., 2015).

unemployment benefits, education subsidies - in response to automation. I consider policy effectiveness separately with respect to a change in prices or the capabilities of automation.

To this extent, I modify a Diamond-Mortensen-Pissarides (DMP) model to include both characteristics of automation, price, and capabilities, as well as skill heterogeneity between workers. The key feature of my model is the wage effect of both prices and capabilities of automation. Similar to routine-biased literature (Acemoglu and Autor, 2011), I model automation as a substitute for low-skill workers, but rather than switch to automation completely, firms use it as a threat in wage negotiations. If the price of automation declines or if there is an expansion of automation capabilities, negotiated wages reflect this change in firms' outside option and adjust downward in partial equilibrium. As a result, automation and workers coexist and could perform the same tasks. For example, a firm could use a cleaning robot on a shop floor, while another firm could use a human worker. The existence of this cleaning robot itself puts downward pressure on workers' wages. In general equilibrium, however, the impact of automation on wages is unclear since changes in automation attract more firms into the sector, and competition for workers could intensify.

To quantitatively evaluate the impact of automation in general equilibrium, I calibrate my model to match labor market statistics in European countries. Using this calibrated model, I simulate steady-state responses of labor market outcomes to a 1% change in each automation characteristic separately while keeping other parameters unchanged. Similarly, I use simulated responses of labor outcomes to changes in policy parameters to gauge their effectiveness as a response to automation.

My simulations yield several results. First, I demonstrate that two automation characteristics differ in their impact on employment and wages, especially when education does not adjust. I show analytically that with fixed educational shares, a decrease in prices of automation without changes in capabilities of automation leads to an unambiguous increase in the employment rate for both low-skill and high-skill workers in general equilibrium. The mechanism behind this result is as follows: a change in the price of automation increases profits and attracts more firms into a sector. Consequently, the number of firms per non-employed low-skill workers in the sector increases, leading to an unambiguous improvement in the employment rate. In contrast, when the capabilities of automation expand with no changes in price, the employment rate might increase or decrease depending on the existing labor market institutions. Under the calibrated parameters based on several European countries, expansion of automation capabilities leads to lower employment rates similar to the prediction of the routine-biased literature but contrary to the effect of declining prices.

As for wage effects, in partial equilibrium, both prices and automation capabilities negatively affect wages. However, a general equilibrium effect on wages depends on how many firms enter the sector, how large the expected net present value of automation option is, and what labor regulations are in place. Under my calibration, a decline in automation prices and expansion of capabilities lower wages of low-skill workers but increase high-skill wages when education does not adjust.

Second, when individuals adjust their education choices, I show that both a decline in price and an expansion of capabilities of automation increase the educational attainment of workers. Such a response is similar to the labor demand shock literature (Morissette et al., 2015; Black et al., 2005a,b; Basso, 2017), however, the mechanism behind the worker's decision about education is quite different. In my model, workers respond to the lack of wage growth, suppressed wages in the sector rather than the lack of employment opportunities resulting from a displacement by automation. Consequently, with a relatively higher share of educated workers, employment rate, and wages in both sectors increase in response to automation. This result contrasts with the model prediction in which educational shares are fixed.

Third, I also find that labor market policies could exacerbate the negative effect of automation on employment. For example, unemployment benefits and union support help increase low-skill workers' wages, but at the cost of lower employment rate. This finding is consistent with the empirical results of Decreuse and Granier (2013).

As a result of this under-investment in education, despite an increase in wages of affected workers, wage inequality between two groups of workers increases (+0.179%) in the model with endogenous education. Note that when education is fixed, the effect of unemployment support on inequality is positive (-.219%). To reverse this negative impact on inequality, policymakers could consider subsidies for education. Subsidies could boost employment and wages of workers with low education (+0.29% and 0.51% respectively) at a modest cost to other workers (-0.01 and -0.32%) and significantly decrease inequality between two groups (-0.829%).

Finally, I show that the effects of changes in automation on the European labor markets could not be replicated by institutional factors or a shift toward service industries. Between 2005 and 2016, a share of tertiary-educated workers increased by 36%, and employment rates of both high-skill and low-skill workers increased, 1.4% and 2.9%, respectively. I use changes in trade union density, overall employment protection index, and replacement rates as proxies for institutional changes. Altogether, these policy changes could explain only one-third of the education increase. A shift towards services performed by high-skill workers could partially explain a rise in education. However, this shift leads to lower employment rates of both types of workers and higher wage inequality, which is the opposite of what is observed in the data. A decline in the price of automation and an expansion of automation capabilities alone contributes a similar proportion.

As a robustness check, I repeat the simulations of my model with a different elasticity of substitution between high-skill and low-skill sectors and a different search cost parametrization. I find that the effect becomes larger in magnitude when the elasticity of substitution is higher, while a different parametrization of search cost does not affect sensitivity results. Additionally, I calibrate and simulate the model for each country individually and then aggregate across countries with no reversals in the effect signs. Aggregated results are quite similar in magnitude to the baseline calibration.

The paper proceeds as follows. In the next section, I discuss the related literature. Section 3 details a model and analyzes the effects of automation on the employment rates and wages in the model. In Section 4, I evaluate the elasticity of labor market response on the steady-state responses to the technological change and labor market policies. Section 5 concludes.

2 Related Literature

This paper builds upon the previous literature on technological change as a driver of labor market changes. Both skill-biased (SBTC) and routine-based technological change (RBTC) literature emphasize employment and inequality effects. In the SBTC canonical model, technology enhances the productivity of skilled workers (where skill is synonymous with education) and drives the labor demand for this group of workers. With a complementarity between skilled and unskilled workers[2], this also leads to an increase in demand for unskilled workers, driving wages of both groups up. However, with a scarce supply of skilled workers, their wages grow faster than wages of unskilled workers, and, consequently, inequality between the two groups rises (Goldin and Katz, 2008). After 2000, the SBTC canonical model explains a significantly lower proportion of wage growth divergence across educational groups (Autor et al., 2020). One of the proposed explanation is that technology becomes more labor-displacing, especially for low-skill workers (Acemoglu and Autor, 2011). When automation becomes available, labor demand declines, and workers are forced to take low-paying jobs. The result of this process is the polarization of employment and wages (Goos et al., 2009), with surging inequality. Autor and Salomons (2017), however, find that in the last thirty years, overall employment has not declined in response to

[2]with low elasticity of substitution, between 1 and 2.5

technological change among the OECD countries, suggesting that technology also spurs growth in new occupations

Acemoglu and Restrepo (2016) incorporates this dual impact of technology into the model where technological progress is represented by two different processes: a worker replacement by automation and the creation of more complex tasks performed by human workers. In a static model with fixed capital and exogenous technology, employment, wages, and labor share decrease with automation, while the creation of new tasks works in the opposite direction. With endogenous technology, automation decreases the relative labor cost of production, making labor attractive as input and discouraging further automation. In this paper, I treat automation as exogenous while allowing for endogenous education in the long run. Both substitution and job creation effects of automation are present, but automation has an additional effect on wages. In my model, firms use automation to negotiate wages down. Overall, while the employment effect is positive, wage growth is suppressed (it does not grow as much as in the traditional model).

Several studies incorporate automation into a search and matching framework. A model by Cords and Prettner (2018) is similar to the RBTC framework in its treatment of technology and its prediction of the negative effect on both employment and wages of low-skill workers. The opposite, positive, employment effect is in the center of the analysis by Guimarães and Gil (2019b) and Leduc and Liu (2019). Both papers are one-sector models, but the firms' behaviors are different. In Guimarães and Gil (2019b) firms *choose to automate* and not to enter the labor search if their productivity is high enough. In Leduc and Liu (2019) firms *attend a labor market first* and if the search is unsuccessful, firms either automate or continue to search. Although automation in their model affects workers' wages, I expand their one-sector model to include skill heterogeneity and education choices.

This paper also contributes to the discussion of the effect of technology on the workers' power. Stansbury and Summers (2020) identify technological change as one of the sources contributing to the decline in workers' power. They argue that an institutional change, a change in management practices, and incentives contribute most to a decline in workers' bargaining power, especially in the US. In this paper, I argue that advancement in automation plays a meaningful role in decreasing effective worker's power and, consequently, their wages. Moreover, this effect of automation on bargaining power could significantly decrease the effectiveness of policy interventions aimed to correct institutional changes. For example, I show that union support by the government could improve wages but at the cost of lower employment, especially in the model with no education adjustment.

In its investigation of policy effectiveness, this paper relates to papers on the interaction between technology and labor market policies. Hornstein et al. (2007) shows that labor policy interacts with technological change and could affect the magnitude of the technological impact. In the model with endogenous education and endogenous technology, Prettner and Strulik (2017) shows that redistributive taxation and a robot tax do not improve the outcomes of low-skill workers. The former policy leads to lower educational attainment, while the latter reduces overall employment and leads to slower growth. Using model simulations, similar to these papers, I show that policy could mitigate or exacerbate the effect of automation. Moreover, I caution that the policy instruments should be carefully chosen to account for the nature of automation advancement and policy goals. Specifically, if the advancement of automation lowers employment of low-skill workers, then, the policy instrument that exacerbates the loss of jobs for these workers should be balanced with another policy.

3 The Model with Automation and Skill Heterogeneity

I extend the two-sector DMP model to include automation and skill heterogeneity. Economy is populated by two types of workers who are classified based on their education as H-type and L-type if they do or do not obtain tertiary education. Workers are either employed, producing one unit of good i that generates endogenously determined p_i units of revenue, $i \in \{H, L\}$, or they are unemployed receiving unemployment value b_i. Suppose there is proportion μ of workers who are H-type. This proportion will be endogenized in later sections. The common discount factor for workers and firms is ρ.

Two intermediate goods sectors, H and L, are combined into a final good using constant elasticity of substitution (CES) production function with elasticity σ. I assume that automation as an alternative to labor input available only in sector L. I characterize automation with two parameters: capabilities of automation φ and price of automation ξ.[3] Parameter φ represents a current state of capabilities of automation, for example, whether a call-center worker could be substituted by automation. An increase in φ then is an expansion of capabilities of automation, or, in other words, an increase in functions and tasks that automation could perform. Price of automation ξ is a use cost or rental cost of automation, thus, it is paid to an owner of automation each period. (Owners of automation are not modeled explicitly in my model, they do not optimize

[3] Acemoglu and Restrepo (2016) also uses two parameters to characterize technology: proportion of automatable tasks (I in their notation) and rental rate of capital (R).

revenue but rather receive rental cost and spend it on the consumption final good.) For simplicity, both parameters of automation are exogenous and common across all firms in the sector.

I include job protection and unemployment benefits as policy instruments. Job protection, - or rather dismissal protection legislation - is represented by firing taxes (T) and separation rates (δ_L, δ_H). A more stringent protection corresponds to higher taxes and lower separation rates.[4] Generous unemployment benefits are reflected in replacement rate, which is a percentage of wages to which unemployed workers are entitled. Education support as a policy is incorporated in the long run model where education response is endogenous.

3.1 Model

Matching. To produce an output, firms in each sector should search and match with an input. A match with automation in sector L is exogenous. Parameter φ, $0 < \varphi < 1$, which I use to characterize current capabilities of automation, also captures the probability of a match with automation. Depending on education, workers choose a labor market where to search for a job, i.e. labor markets are separated by a worker type.[5] The employment status of a worker, either employed or unemployed, is determined by a search and matching process. Number of matches between worker and firm in each sector is defined by the matching function $m_i(u_i, v_i)$, where u_i denotes unemployment rate of workers of type i and v_i is the ratio of firms searching for an input to number of workers of type i. In each market i, market tightness is a ratio of searching firms to unemployed workers, $\theta_i = v_i/u_i$. Then, a job finding rate for a worker of type i is $f_i = m_i/u_i$, and a firm searching for an input is matched to an unemployed worker with a rate $q_i = m_i/v_i$. Both rates are functions of market tightness with $q'(\theta_i) < 0$ and $f'(\theta_i) > 0$. Under the constant returns to scale of the matching function, it follows that $f_i = \theta_i q_i$.

Worker value functions. Let J_i^U denote the value of unemployment, while J_i^E denotes the value of employment in sector i for a worker of skill i. An unemployed worker of type i receives flow value b_i and finds a job at rate f_i. J_i^U satisfies

$$\rho J_i^U = b_i + f_i(J_i^E - J_i^U). \tag{1}$$

[4] With higher job protection regulations, it is harder for employers to dismiss a worker, hence, it leads to lower separation rates.

[5] An L-type worker is not productive in H sector and vice versa.

Let w_i denote the wage worker i in sector i receives under the Nash bargaining solution. An employed worker earns wage w_i, pays income tax τw_i and might experience an exogenous separation shock at rate δ_i transitioning to unemployment.

$$\rho J_i^E = w_i(1-\tau) + \delta_i(J_i^U - J_i^E). \tag{2}$$

Firm value functions. Automation has the same productivity as L workers and is provided by technology monopolist (not explicitly modeled). An idle firm in sector i searches for input of type $i \in \{H, L\}$ and pays a per period search cost of κ_i. A firm in sector L receives a rental offer for automation capital at exogenous rate φ or it meets with a worker at a rate q_L. A rental offer is a take-it-or-leave-it offer at an exogenously set price ξ. Let J_i^V represent the value of searching for input of type i, and J_i^F denotes the value of producing with a worker. J^M denotes the value of producing with automation in sector L. J_i^V satisfies

$$\begin{aligned} \rho J_L^V &= -\kappa_L + \varphi_L J^M + q_L J_L^F. \\ \rho J_H^V &= -\kappa_H + q_H J_H^F. \end{aligned} \tag{3}$$

Here, I assume that the value of the firm's outside option is equal to zero, $J_i^V = 0$, which is consistent with a common free entry condition.

The value of producing with automation in L sector, J^M, is a flow value of output less the rental price (Eq.(4)). Note that separation rate from automation might be different from the separation rate from a worker, $\delta_m \neq \delta_L$.

$$J^M = \frac{p_L - \xi}{\rho + \delta_m}. \tag{4}$$

If a firm in sector i produces with a worker, the value is a flow output value less paid wages and expected value of firing tax T.

$$J_i^F = \frac{p_i - \delta_i T - w_i}{\rho + \delta_i}. \tag{5}$$

Given the free entry condition ($J_i^V = 0$), input demand in each sector is then:

$$\kappa_H = q_H \frac{p_H - w_H - \delta_H T}{\rho + \delta_H} \tag{6}$$

$$\kappa_L = q_L \frac{p_L - w_L - \delta_L T}{\rho + \delta_L} + \varphi \frac{p_L - \xi}{\rho + \delta_M}. \tag{7}$$

I further assume that parameters satisfy the following two constraints. The first assumes positive profitability of using automation to rule out the case where no firms use automation:

$$p_L - \xi > 0. \tag{8}$$

The second constraint limits the overall surplus for firms with automation capital:

$$\kappa_L - \varphi \frac{p_L - \xi}{\rho + \delta_m} > 0. \tag{9}$$

The same constraint also ensures that expected surplus of vacancy filled with a worker is positive, $q_L J_L^F > 0$.

Wage determination. Let $\gamma \in (0, 1)$ denote the workers' bargaining power, which is the same in both sectors. Each matched worker-firm pair engage in wage negotiations via the Nash bargaining process. Thus, wage w_i is a solution to optimization problem[6]:

$$\max_{w_i} (J_i^E - J_i^U)^\gamma (J_i^F - J_i^V)^{1-\gamma}. \tag{10}$$

The corresponding wage is a sum of foregone unemployment value and a proportion of surplus from the match with a firm. In sector H, wages unambiguously increase in market tightness, while in sector L the effect of market tightness is undetermined given that firm forgoes the option to wait and match with automation.[7] Thus, I refer to $(-\gamma\theta_L\varphi J^M)$ as wage penalty. The wage penalty is increasing in market tightness; thus, all else equal, wages are lower for L workers than they would have been in a standard model. Moreover, wage penalty increases with advancement of automation, both with increasing substitution of workers (higher φ) or with declining prices of automation (lower ξ).

$$w_H(1 - \tau(1-\gamma)) = b_H + \gamma(p_H - b_H - \delta_H T + \theta_H \kappa_H), \tag{11}$$

$$w_L(1 - \tau(1-\gamma)) = b_L + \gamma(p_L - b_L - \delta_L T + \theta_L \kappa_L) \underbrace{-\gamma\theta_L\varphi J^M}_{\text{Wage penalty}}, \tag{12}$$

Employment levels. At a steady-state equilibrium, the flows from and into unemployment are equal. Let $u_L = U_L/(1-\mu)$ denote the unemployment rate of L workers, while $u_H = U_H/\mu$ denotes the unemployment rate of H workers, where U_i denotes a number of unemployed workers of type i. Then, in equilibrium, unemployment rates for each

[6] See Appendix A.1 for wage equation derivation

[7] $\partial w_L/\partial\theta_L > 0$ if and only if a foregone option of automating in the future period is larger than price decline (in absolute value) $\kappa_L - \varphi J^M > -\partial p_L/\partial\theta_L \left(1 - \varphi\theta_L/(\rho + \delta_m)\right)$

category are the same as in standard search and matching models:

$$u_i = \frac{\delta_i}{\delta_i + f_i}. \tag{13}$$

Final good sector. Intermediate goods from both sectors and physical capital are combined into a final consumption good via production function:

$$Y = A\left(\alpha^{1/\sigma} Y_L^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^{1/\sigma} Y_H^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{14}$$

where α measures the importance of the low-skill sector in production of the final good, σ governs elasticity of substitution between intermediate sectors, and A is a total factor productivity.

Under perfect competition, equilibrium prices of intermediates are given by

$$p_L = A^{(\sigma-1)/\sigma}\Big(\alpha Y/Y_L\Big)^{1/\sigma}, \qquad p_H = A^{(\sigma-1)/\sigma}\Big((1-\alpha)Y/Y_H\Big)^{1/\sigma} \tag{15}$$

I normalize the price of the final good p to 1. Prices of intermediate goods depend on the level of production in each sector. If level of production in sector i increases, price of output in sector i, p_i, decreases while it increases in sector j[8].

Production levels. Production levels in each intermediate sector depend on number of employed individuals in each sector and number of firms with automation in sector L. To determine the level of production in sector L, I define the flow of vacancies in this sector. Traditionally, flow of workers from and to unemployment and flow of vacancies are the same, since the number of employed persons is the same as a number of producing firms. However, with the alternative input, automation, this is no longer true. Now, the number of producing firms $\mathcal{N}_L$ is higher than the number of employed individuals. Thus, in equilibrium a number of firms exiting production stage should be equal a number of firms entering that stage:

$$(\delta_L + \delta_M)\mathcal{N}_L = V_L(q_L + \varphi), \tag{16}$$

where $V_L = v_L(1-\mu)$ represents the number of vacancies opened by L firms. Equation (16) together with equation (13) for L-type workers also ensures that number of firms with automation is stable in equilibrium. Using the definition of market tightness, I

[8] $\partial p_i/\partial Y_i < 0$, $\partial p_i/\partial Y_j > 0$. See Appendix A.2

can rewrite $V_L = \theta_L u_L(1-\mu)$. Then, production levels in each sector are given by

$$Y_H = \mu(1-u_H) \tag{17}$$
$$Y_L = (1-\mu)((1-u_L)\delta_L + \theta_L u_L \varphi)/(\delta_L + \delta_M). \tag{18}$$

Education decision. In the short run, I assume that education shares are fixed. In the long run, an education decision is endogenous. Individuals decide to acquire education by comparing the values of entering the labor market with and without education. Workers face the cost of education c and invest in education until the values of being unemployed with and without education are equal.

$$J_H^U - J_L^U = c \tag{19}$$

Budget constraints. The government taxes both employed workers and firms who lay off workers and redistributes the revenue in the form of unemployment benefits. A government collects income tax τ and firing taxes T and distributes unemployment benefits b_i to balance its budget.

$$\begin{aligned}&\tau(w_H(1-u_H)\mu + w_L(1-u_L)(1-\mu)) + T(\delta_H(1-u_H)\mu + \delta_L(1-u_L)(1-\mu)\\ &\quad = b_H u_H \mu + b_L u_L(1-\mu).\end{aligned} \tag{20}$$

Feasibility constraint for the whole economy then is the sum of expenditures for all agents in the economy, including after-tax wages, unemployment benefits, search costs, rental cost of automation and education costs (when using the full model).

$$\begin{aligned}Y = &\underbrace{(w_H(1-u_H)\mu + w_L(1-u_L)(1-\mu))(1-\tau)}_{\text{After-tax wages}} + \underbrace{b_H u_H \mu + b_L u_L(1-\mu)}_{\text{Unemployment benefits}}\\ &+ \underbrace{\kappa_L v_L(1-\mu) + \kappa_H v_H \mu}_{\text{Search costs}} + \underbrace{\xi(Y_L - (1-\mu)(1-u_L)\delta_L/(\delta_L+\delta_M)}_{\text{Automation rental cost}} + c\mu\end{aligned} \tag{21}$$

Equilibrium. A steady-state equilibrium in the baseline model for a vector of key endogenous variables $(\theta_i, u_i, w_i, p_i, Y_i)$ is determined by the following system:

(i) input demand (6) and (7),
(ii) wage equations (11) and (12),
(iii) unemployment flows (13),
(iv) price equations (15),
(v) production levels (17) and (18),

subject to constraints (20) and (21).

In the full model, a vector of endogenous variables includes a share of tertiary educated μ - $(\mu, \theta_i, u_i, w_i, p_i, Y_i)$ - and the system of equations also include education decision (Eq.(19)).

3.2 Analytical results for the model without education adjustment

The baseline model outlined above encompasses several mechanisms of technological impact. While an employment effect to a change in automation prices is relatively simple to derive from this model, the impact of the expansion of capabilities (φ) depends on the elasticity of price to this parameter as well as on institutional parameters such as workers' bargaining power (γ) and job protection (separation rate δ_L). The model also includes a wage effect through a wage penalty (See Eq.(12)). The equilibrium effect of technological change on wages has to be assessed with numerical methods.

Proposition 1 (Employment effects)**.** *Employment effect depends on the changes in automation characteristics and labor market institutions:*

(i) A decrease in prices of automation ξ leads to higher employment rates in both sectors, $d\theta_H/d\xi < 0$, $d\theta_L/d\xi < 0$.

(ii) An expansion of capabilities of automation, φ, has a positive effect on employment in H sector $d\theta_H/d\varphi > 0$. Employment in L sector increases $d\theta_L/d\varphi > 0$ if the intermediate price elasticity with respect to φ is smaller than adjusted expected profitability of automation $-\epsilon_{\varphi}^{p_L} < \varphi J^M/(p_L\Sigma_L)$, where $\Sigma_L = (1-\gamma)q_L/\Big((\rho+\delta_L)(1-\tau(1-\gamma)) + \gamma f_L\Big)$[9] and J^M is given by Eq.(4).

Proof. See Appendix A.3.3 and A.3.2. □

The result in (i) is intuitive. A decrease in prices of automation attracts firms into the L sector, increasing market tightness, and job finding rate for L-type workers. Consequently, it leads to a higher level of production in the sector. Since the two sectors are complements in the final good production, demand for good H rises, leading to higher employment rates for H-type workers. With higher competition, prices of intermediate goods and matching rates with workers (q_i) decline until the zero-profit condition is satisfied.

In case of (ii), expanding capabilities of automation increase level of production in sector L, Y_L (see Eq.(18)) and, consequently, decrease a price of good p_L. The

[9] $\partial\Sigma_L/\partial\gamma < 0, \partial\Sigma_L/\partial\delta_L < 0$

elasticity of a price response in conjunction with the adjusted expected profitability of automation determines the equilibrium effect on employment in sector L. Moreover, the labor market institutions such as worker's bargaining power γ and job protection (δ_L) also interact with technology and may amplify or mitigate its impact.

Proposition 2 (Wage effects)**.** *Effect of technical change on wages depends on elasticity of price changes to automation parameters:*

(i) Wages of H-type workers are increasing in capabilities of automation φ if $\frac{dp_H}{d\varphi} > -\frac{d\theta_H}{d\varphi}\kappa_H$

(ii) Wages of H-type workers are increasing in automation prices ξ if $\frac{dp_H}{d\xi} > -\frac{d\theta_H}{d\xi}\kappa_H$

(iii) Wages of L-type workers are increasing in capabilities of automation φ if $\frac{dp_L}{d\varphi}(1 - \frac{\varphi\theta_L}{\rho+\delta_M}) > -\frac{d\theta_L}{d\varphi}(\kappa_L - \varphi J^M) + \theta_L J^M$

(iv) Wages of L-type workers are increasing in automation prices ξ if $\frac{dp_L}{d\xi}(1 - \frac{\varphi\theta_L}{\rho+\delta_M}) + \frac{\varphi\theta_L}{\rho+\delta_M} > -\frac{d\theta_L}{d\xi}(\kappa_L - \varphi J^M)$

Proof. See Appendix A.3.4 and A.3.5. □

Proposition 2 shows that the wage effect depends on the elasticity of prices and market tightness with respect to automation parameters. The impact of changes in automation parameters on wages of H-type workers is straightforward: if the price change p_H in response to technology advancement is larger than the change in the present value of search costs, then wages increase. For example, a decline in automation price could lead to lower wages of H workers if competition among entrants into sector H leads to a larger decline in revenue than the gain from a match with a worker (savings from abandoning the search $\kappa_H d\theta_H / d\xi$).

These two propositions illustrate that the evaluation of automation impact requires numerical analysis even with a baseline model. Evaluation in the full model with endogenous education cannot be conducted without numerical methods.

4 Quantitative analysis

I parametrize the model for the average values of European countries to understand the response of employment and wages to changes in automation for each group of workers.

4.1 Calibration

I make several simplifying assumptions to proceed with calibration. First, the matching function is assumed to be Cobb-Douglas with standard properties, $M_i = \chi_i U_i^{\eta} V_i^{1-\eta}$.

Second, the gross cost of automation is set to generate a 2% profit similar to Leduc and Liu (2019). Third, the depreciation of automation is set to 12% per year. Several parameters are tied to the data or are taken from previous studies. I set a quarterly discount rate ρ to match the annual rate of 4%. To define unemployment benefits, I use net replacement rates from OECD (2017). Unemployment benefits b_i are set to equal replacement rate times wages w_i. Data on severance pay legislation allows me to calibrate firing tax T (see Appendix B).

Separation rates for each type of worker are calculated based on the average tenure statistics from OECD and the US separation rates from Chassamboulli and Palivos (2014) (see Appendix B for details on calculation). Search costs κ_i are set to 50% of wages.[10] Bargaining power of workers γ and elasticity of matching function η are both set to 0.5 as in Pissarides and Petrongolo (2001). Elasticity of substitution σ between two intermediate sectors, H and L, is set to 2.[11] Section 4.5 discusses alternative parametrizations for elasticity of substitution σ and search costs κ_i. I normalize the price of the final good to 1. Income tax τ is determined by the government budget constraint (Eq.(20)).

Remaining parameters $\{\varphi, \chi_H, \chi_L, \alpha, A\}$ are calibrated jointly to exactly match data on employment rates for both categories of workers, labor share, education wage premium, and share of the population with tertiary education (Table 1). The sources and moments calculation are detailed in Appendix B. In my model, labor share, ls is defined as a ratio of all wage income to output:

$$ls = \frac{w_H\mu + w_L(1-\mu)}{Y} = \frac{(\tilde{w})}{Y} \tag{22}$$

Calibration results for the baseline model are shown in Table 2. I repeat the calibration procedure with the same targets for the full model, i.e., education is endogenous. The parameters for the two models are compared in Appendix C.3.

4.2 Impact of capabilities and prices of automation on labor market

My primary object of interest is the sensitivity of labor outcomes to technological change. To this extent, I simulate a 1% increase in technology availability (φ). Then, I repeat the simulation for a 1% decrease in automation cost (ξ), leaving all other parameters unchanged. The new steady-state equilibrium is compared to the initial

[10] Search costs in the proposed model are not purely for hiring workers as in a standard search model, but for finding an input, either worker or automation

[11] Several studies estimate this elasticity between 1.5 and 2.5, see the discussion in Acemoglu and Autor (2011)

Table 1: Matched moments

Indicator	Value	Source / Comment
Wage premium	2.041	SILC
Employment rate, low-skill	0.683	ILO
Employment rate, high-skill	0.850	ILO
Share of tertiary educated	0.298	average 1999-2019 ILO
Labor share	0.634	EUKLEMS
Average GDP per capita	1	Normalize average to 1

Notes: See Appendix B for details.

one, and all labor market outcome responses are converted to percentage deviations from this initial steady state. Thus, the reported sensitivity of steady-state outcomes could be interpreted as elasticity to each parameter.

I define additional measures of welfare for each type of worker and overall welfare. Welfare for a worker of type i is a weighted average of after-tax wages and unemployment benefits. Overall per-capita welfare is then a weighted average of welfare measures of both types of workers.

$$\mathcal{W}_i = w_i(1-\tau)(1-u_i) + b_i u_i \forall i \in \{H, L\} \tag{23}$$

$$\mathcal{W} = \mu \mathcal{W}_H + (1-\mu)\mathcal{W}_L \tag{24}$$

Table C1 shows the sensitivity of labor market outcomes for the short-run (baseline), while Table C2 reports results for the long-run when education decisions are endogenous.

I start with the description of the results for the model without educational adjustment. One might think that a lower automation cost leads to a lower employment rate of L-type workers, given that now automation is cheaper to obtain for firms. This intuition is only valid if the number of firms is held constant. However, in general equilibrium, as analytical results in section 3.2 show, lower cost of automation attract more firms into the sector, resulting in better employment opportunities for L-type workers. A 1% decrease in the cost of automation leads to a 0.766% increase in employment rate in the L sector. However, general equilibrium allows a positive, as well as negative, effect of the expansion of automation capabilities (increase in φ) on employment (Proposition 1).

Current calibration shows a result consistent with the RBTC framework: a 1% increase in automation availability leads to a 0.092% decrease in the employment rate of affected workers. Note that this impact is relatively small in magnitude, thus, only a drastic innovation with a jump in the number of automatable tasks could significantly affect the employment rate of affected workers. However, the history of technology

Table 2: Parameters for the model without education adjustment (baseline)

Parameter	Description	Value	Source / Comment
Measured from data or adopted from previous studies			
γ	worker bargaining power	0.5	Pissarides and Petrongolo (2001)
η	matching parameter	0.5	Hosios condition
ρ	quarterly interest rate	0.0099	Match OECD average annual interest rate of 4% over 1990-2010 period
δ_M	separation rate of automation	0.003	12% per year
δ_L	separation rate L	0.032	See Appendix B
δ_H	separation rate H	0.018	See Appendix B
b_L	replacement ratio	0.374	OECD Benefits and Wages
b_H	replacement ratio	0.374	OECD Benefits and Wages
κ_H	vacancy cost in sector H	0.6496	Set to equal 50% of w_H
κ_L	vacancy cost in sector L	0.318	Set to equal 50% of w_L
ξ	rental rate of technology	0.7506	Set to give 2% profit (Leduc and Liu, 2019)
T	firing tax	0.1763	set to 23.5% of average wages (ILO Severance pay data)
Jointly calibrated to match data moments (Table 1)			
χ_L	matching efficiency L	0.079	calibrated
χ_H	matching efficiency H	0.111	calibrated
α	share of low-skill sector	0.368	calibrated
φ	probability of a match with automation	0.106	calibrated
A	total factor productivity	1.188	calibrated

adoption shows a gradual introduction of new technology uses, which gives workers time to adapt by acquiring education. Thus, a long-run model with an educational adjustment is more suitable for analyzing the impact of the expansion of automation capabilities.

At the same time, wages of L-type workers respond similarly to two types of technology change. With the expansion of automation capabilities, wages decrease by 0.091%, while with a lower automation cost, wages decline by 0.298%. Despite a negative wage effect of prices, average welfare for L-type increases by 0.282%. In contrast, in responses to the expansion, both the employment rate and wages decrease, resulting in a welfare decline. Figure 1 plots the elasticity of employment rates and wages in the model without education (the first two rows in Table C1).

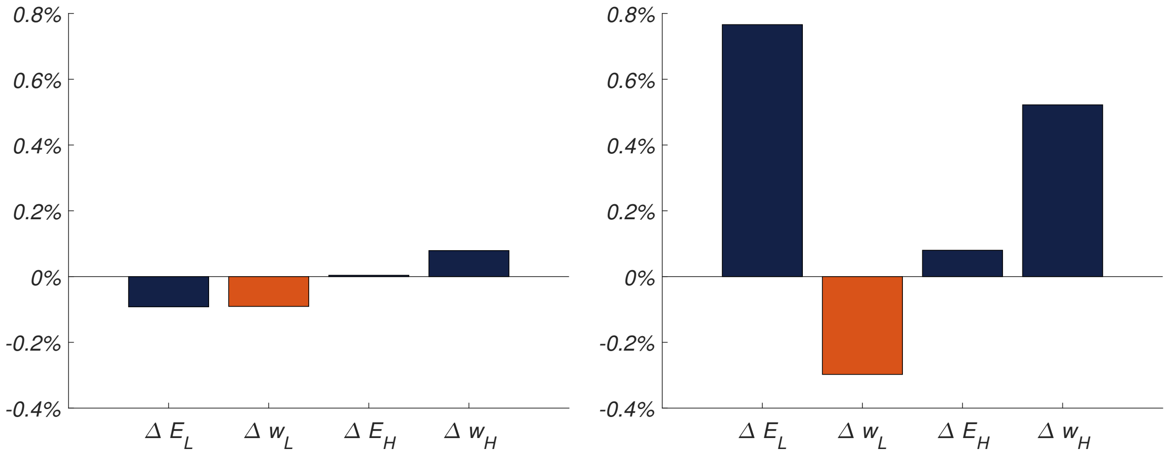
As for H-type workers, employment rates and wages increase in response to automation, with the employment effect being relatively small (0.004% and 0.080%) compared to wages (0.079% and 0.522%). Consequently, the welfare of H-type workers increases when automation advances (0.064% and 0.8%), but its increase is significantly larger in magnitude than L-type workers. As a result, inequality between the two groups of workers measured by the wage ratio, welfare difference, and labor share increases. Note that all outcomes' responses to prices are more extensive in magnitude than responses to an automation expansion. Thus, a slowdown in the price of automation decline would also coincide with smaller changes in workers' labor market outcomes.

The negative employment effect of technological change has been prevalent both in SBTC and RBTC literature. Hornstein et al. (2007) and Cords and Prettner (2018) predict a rise in unemployment of affected workers, while the results in Guimarães and Gil (2019a) are consistent with empirical evidence on the positive employment effect of technology (Autor and Salomons, 2017). However, in most models, employment is positively correlated with wages. Those models require a change in some institutional parameters like job protection unionization rates to obtain diverging trends of stagnating or declining wages in conjunction with non-decreasing employment. As simulation results show, the baseline model could accommodate such diverging trends between employment and wages.

In the long run, responses of labor market outcomes to technical change differ from the short-run (Table C2). First, technical change stimulates educational investment, consistent with the literature (e.g., Prettner and Strulik (2017)). Education response is more sensitive to price declines than to the expansion of capabilities: 0.279% vs. 0.163%, respectively. Second, this model's wage response is positive to both prices and availability, contrary to the result in the short run. Third, elasticity of wages and employment to automation expansion (φ) is practically zero (see Fig. 2). Thus, educational response balances out employment and wages responses, leading to slightly smaller inequality between two groups of workers (relative wages decreases by 0.005%). Fourth, the sensitivity to price remains consistently higher than the sensitivity to the expansion. For example, the employment rate of L-type workers increases by 0.251% in response to prices, while in response to the expansion of automation capabilities, it increases only by 0.011%.

Furthermore, while wage inequality increases in the short-run (0.17% and 0.822%), it slightly decreases in the long run (-0.005% and -0.006%). As for the inequality between workers and capital owners (measured by labor share), its increase is significantly less drastic in the long run compared to the short run: a maximum decline in labor share is -0.551% in the baseline model vs. -0.066% in the full model.

To summarize, the effect of automation might differ depending on whether we analyze it in the short or the long run. Specifically, there are stark differences in



(a) Expansion of capabilities of automation ($1\% \uparrow \varphi$)

(b) Decline in price of automation ($1\% \downarrow \xi$)

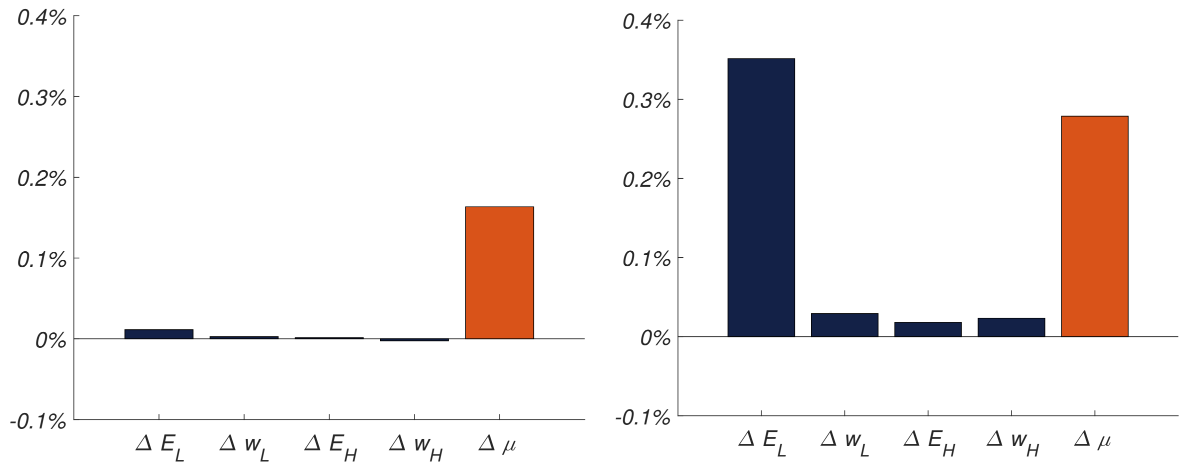
Figure 1: Different impact of automation characteristics on employment in the model without education adjustment (short-run)

Notes: y-axis is a percentage change in outcome listed in x-axis; ΔE_i is a change in employment rate, Δw_i is a change in wages of worker i

responses of wages and inequality between those models. In the short run, wages of L-type workers decrease in response to technological change, and wages of H-type workers increase via complementarity between two sectors. While in the long-run, both groups' wages do increase, the increase in inequality is virtually zero. Additionally, it is worth noting that automation advancement has different effects on the baseline model's employment rate, depending on whether it is a change in the price of automation or a change in capabilities but a similar impact when education is endogenous. In both models, a decline in automation prices significantly affects labor market outcomes more than an expansion of automation capabilities.

4.3 Policy experiments

For both models, I simulate responses to the changes in the following policy instruments: firing tax T, separation rate δ_L, union support via bargaining power γ, and unemployment benefits b_L. Firing tax, union support, and separation rate reflect the strength of employment protection in the economy. Although a separation rate in DMP models usually represents an exogenous productivity shock, I consider a separation rate to reflect existing employment protection in this paper. For example, in Belgium, if a firm decides to dismiss employees, it should notify them at least 30 days in advance, and in some cases, the length of a notice period depends on tenure. Other European



(a) Expansion of capabilities of automation ($1\% \uparrow \varphi$)

(b) Decline in price of automation ($1\% \downarrow \xi$)

Figure 2: Education, employment and wages increase in response to changes of automation characteristics in the model with education adjustment (long-run)

Notes: y-axis is a percentage change in outcome listed in x-axis; ΔE_i is a change in employment rate, $\Delta\mu$ is a change in share of tertiary educated

countries have similar dismissal regulations. [12] Taken together, advance notices and severance pay offer more protection for an employee and make it harder for a firm to dismiss workers. As a result, the duration of the match with a worker or tenure increases with more stringent protection.

In simulations, I decrease a separation rate for L-type workers, δ_L, assuming that employment protection is binding for L-type workers. Even though some studies emphasize a connection between regulations and the matching process, I implicitly assume that more stringent protection has no bearing on the matching efficiency parameter, χ_L. As mentioned earlier, I use the rate of severance pay to proxy for firing tax.[13] Severance pay or redundancy pay is offered to laid-off employees, and it varies from country to country. For example, in the UK, employees between the ages of 22 and 40 are entitled to one week's pay for each year of tenure, while in Belgium, every employee receives four-month pay of severance pay.[14] Even though severance pay is usually paid to employees at the time of their dismissal, for simplicity I assume that in my model this firing tax T is paid to the government. In the model, bargaining power γ as a policy instrument reflects the overall support of trade unions and collective bargaining agreements by the government. An increase in γ signifies an increase in collective bargaining coverage via government legislative changes or a bill simplifying

[12] In the United States, there is "at-will" employment, where dismissal can be effective immediately.
[13] Similarly to Hornstein et al. (2007)'s calibration of firing tax
[14] See https://www.eurofound.europa.eu/observatories/emcc/erm/legislation

trade unions' formation.

I simulate a 1% increase in firing tax and bargaining power for both types of workers, a 1% increase in replacement ratio, and a 1% decrease in separation rate for L types only. In the model with education adjustment, I also analyze the responses to one additional policy instrument - educational subsidy, modeled as a 1% decrease in education cost c.

In the baseline model without education adjustment, all policies, except firing tax, lead to higher wages of L-type workers and lower wage inequality. However, the impact on employment varies across instruments. An increase in unemployment benefits and bargaining power leads to higher unemployment, 0.084% and 0.22% respectively.

Two measures of employment protection, higher firing tax, and lower separation rate δ_L have a positive impact on the employment of L-type workers. This positive response of employment could be explained by the fact that with stricter employment protection matches with workers last longer, making it worthwhile for firms to enter and pay a search cost. An increase in bargaining power and unemployment benefits may potentially counteract a wage penalty for L-type workers associated with technological change. Wage elasticity to those two instruments, 0.177% and 0.383%, is higher than the decline in wages resulting from technology (-0.091% and -0.298%). Note, however, that strengthening of unions works best when technology advances via price decline: a net change in employment and wages would be positive, while the same policy could exacerbate employment decline if used in response to the expansion of technology capabilities.

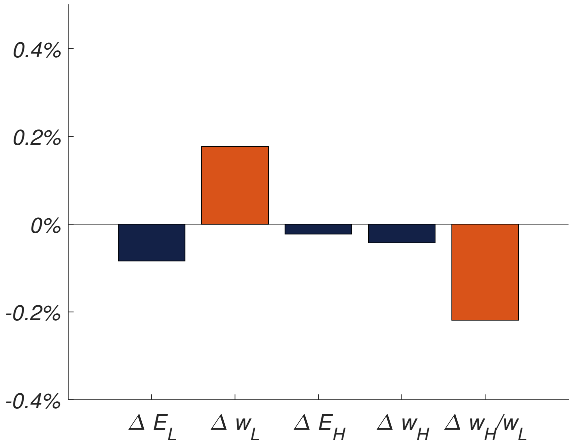
These experiments tell us how much we need to change a policy instrument to mitigate the effect of automation. However, when we choose a policy instrument, we need to be aware of some unintended consequences. For example, to counteract a -2.98% wage decline that results from the 10% decrease in the price of automation, we could increase the replacement rate for low-skill workers by 16.8% or from 37.4% to 43.7%. However, this increase in unemployment benefits would also change a gain in the employment rate of low-skill workers, the rate would increase by 6.25% rather than by 7.66%, or from 68.3% to 72.6% rather than to 73.5%. The consequences for the employment rate will be more dire if we use the same policy to counteract an expansion of the capabilities of automation. A 10% increase in capabilities of automation, or in the context of my model, an increase in the probability of a match with automation, leads to a decrease in employment rate from 68.3% to 67.7%. If we increase the replacement rate by 5.1% to counteract wage decrease, the employment rate decreases further to 67.4%.

I repeat the same simulations for the model with education adjustment. First, in this model, all policy instruments' effects have a larger effect on employment compared to the model without education adjustment, but the wage effects are smaller. Second, education decreases in response to three out of five instruments. Higher unemployment benefits, higher union support, and better employment protection lead to lower educational attainment, while educational subsidy and higher firing taxes have the opposite effect. A decrease in education in my model is also consistent with empirical evidence from Decreuse and Granier (2013) who report that more generous unemployment leads to lower educational investment.

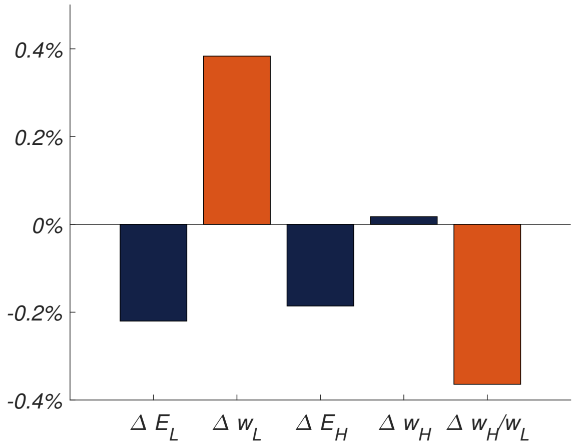
Among the five policies I look at, the subsidy has the largest effect on education: a 1% decrease in educational cost leads to a 1.394% increase in the share of the population with tertiary education. Consequently, wage inequality between two groups of workers declines (-0.829%) as more workers enter the H labor market; however, another measure of inequality, labor share, changes only modestly (+0.068%). In sum, subsidizing education helps reduce inequality between workers, but it does not reduce inequality between workers and capital owners. This result means that even with a declining labor share in the economy, we might see lower inequality between workers. Third, when educational adjustment is accounted for, using unemployment benefits and union support to boost wages of low-skill workers could lead to a result opposite of what was intended: wage inequality between high- and low-skill workers increases as a direct consequence of lower educational attainment.

In conclusion, simulation results demonstrate that the impact of policy on labor outcomes differ in the short run versus the long-run. For example, the elasticity of response to policy is larger in the long-run rather than in the short-run. Moreover, the policy might differently affect employment, wages, and inequality in the long-run. It implies that the choice of policy instrument depends on a policy target. For example, higher unemployment benefits could worsen inequality in the long run but improve it in the short run.

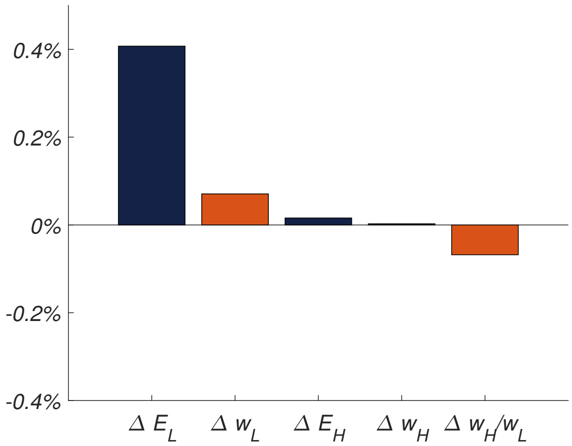
Guimarães and Gil (2019a) argue that the impact of labor market policies is insignificant compared to the technological impact. In their model, labor market outcomes have smaller elasticities to policy instruments, however, the role of that policy is not easily dismissed in my model with an educational adjustment. With simulations, I show that this is true in the short run without educational adjustment and only for the expansion of automation capabilities. In the long run, policy sensitivity increases above the sensitivity to technology. In Prettner and Strulik (2017), redistribution policy in form of transfers reduces education similarly to job protection in my model. The authors show that with both endogenous education and technology, L-type worker



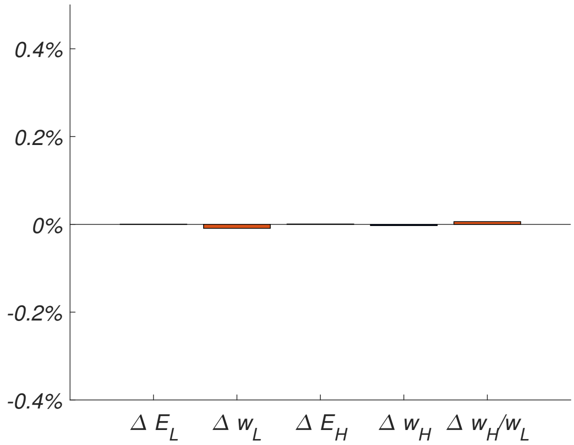
(a) Increase in unemployment benefits ($1\% \uparrow b_L$)



(b) Increase in union support ($1\% \uparrow \gamma$)



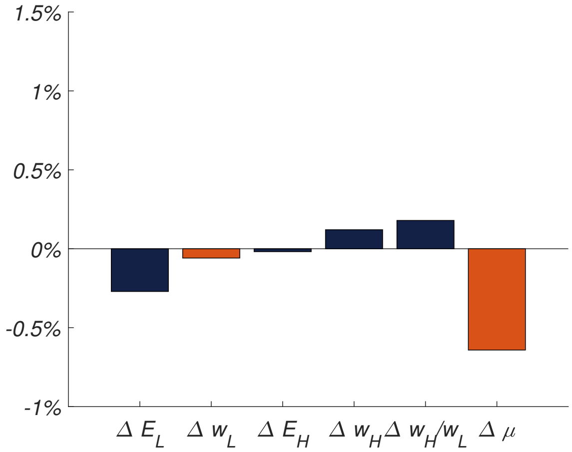
(c) Increase in job protection ($1\% \downarrow \delta_L$)



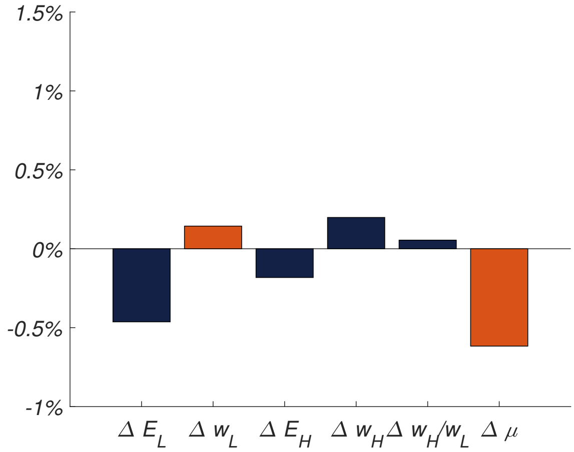
(d) Increase in job protection through penalties ($1\% \uparrow T$)

Figure 3: Policy experiments, model without education adjustment

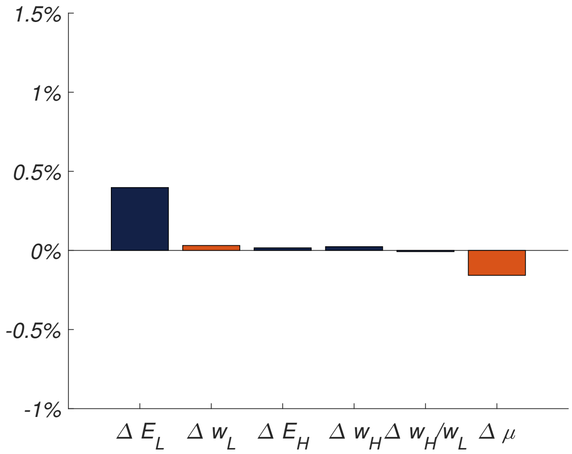
Notes: y-axis is a percentage change in outcome listed in x-axis; ΔE_i is a change in employment rate, $\Delta w_H/w_L$ is a change in relative wages



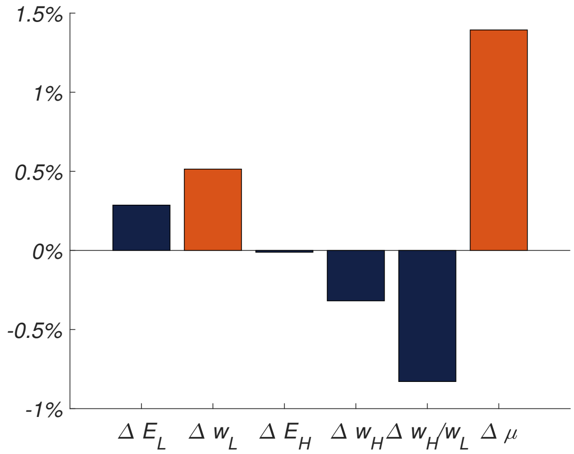
(a) Increase in unemployment benefits
(1% ↑ b_L)



(b) Increase in union support
(1% ↑ γ)



(c) Increase in job protection (1% ↓ δ_L)



(d) Increase in education subsidies (1% ↓ c)

Figure 4: Policy experiments, model with education adjustment

Notes: y-axis is a percentage change in outcome listed in x-axis; ΔE_i is a change in employment rate, $\Delta\mu$ is a change in share of tertiary educated, $\Delta w_H/w_L$ is a change in relative wages income is hard to improve. They conclude that only with fixed educational attainment improvement is possible. I show that with exogenous technology but endogenous education, improvement in the welfare of L-type workers is possible with educational subsidies.

4.4 Contribution of automation to labor market changes in Europe in the 2005-2016 period

In this section, I describe the changes in labor market outcomes between 2005 and 2016 and evaluate the significance of the development of automation for those changes. The analysis is based on the average changes across the eight countries listed in Appendix B.

Changes in labor market outcomes include a change in educational attainment μ, in relative wages $\Delta w_H/w_L$, employment rates E_H, E_L, and GDP per capita. Between 2005 and 2016, the average share of workers with tertiary education has increased significantly from 26.5% to 36.08% (36% increase), and relative wages declined by 9%. However, wage growth has not caught up with productivity growth (See Fig. C1).

Moreover, despite an enormous increase in the number of people with tertiary degrees, the employment rate of H-type workers is higher in 2016 by 1.4% than in 2005. The employment rate of workers with education below tertiary also increased (2.9%). Over this period, GDP per capita has grown by 5.1% (1% increase in GDP per worker), and labor share has barely changed (-0.57%). To evaluate how much of these changes could be explained by automation, I calibrate the full model using 2005 moments and simulate a change in each parameter.

Among factors that could contribute to the labor market changes there are institutional factors, a structural shift to services, and automation. Some researchers argue that institutional changes are a primary driver of the worsening of workers' welfare, especially in the US (Stansbury and Summers, 2020). Among the countries included in the sample (see Appendix B), there is an observed decrease in replacement rates, trade union density, collective bargaining coverage, and overall employment protection during the 2005 to 2016 period. Given that replacement rates data stops in 2013, I assume that 2016 replacement rate is the same as the 2013 one. A decrease in replacement rate between 2005 and 2013 is 4 percentage points (from 38% to 34%).

While OECD replacement rate statistic is averaged across all types of workers, in the model simulation, I assume that this reduction in replacement rate is for workers with tertiary education (H-type) only, while L-type workers have the same replacement rate in 2016 as in 2005. I associate trade union density and collective bargaining coverage statistics with the worker's bargaining power parameter γ in the model and elasticity of a matching function η through the Hosios condition. The overall protection index statistics proxies changes in the separation rate of L-type workers, δ_L, where the lower index is associated with a higher separation rate. Trade union density has dropped from 35.6% to 32.4% (or -8.8%), while collective bargaining coverage decreased on average by 10%. Overall employment protection index has decreased by 4.05%. Table 3 summarizes these observed changes.

While a decline in unionization, lack of legislative support for unions, weakening of employment protections could explain a lagging behind productivity growth of wages, it is unclear how they could explain a rise in educational attainment and a decline in wage inequality between two groups of workers over the same period. In a paper by Acemoglu et al. (2001), a connection between increased education and deunionization is technological change; however, deunionization is an outcome rather than a factor.

Technological explanations are at the heart of the RBTC literature in which a pure substitution of workers by automation reduces the employment of affected workers. However, in the data, we observe a non-decreasing employment rate for those workers. Incorporating the creation of new complex tasks as an additional characteristic of technological change (Acemoglu and Restrepo, 2016) helps resolve this problem. However, that model does not allow endogenous education decisions, education shares are deemed exogenous, therefore, it could not entirely explain a significant growth in educational attainment. In this paper, education responds to changes in automation, as simulation results in the previous section revealed (Table C2).

To quantify the effect of technological change, I use the following strategy. First, since automation price is not directly observed, I use a proxy - a relative investment goods price as in Karabarbounis and Neiman (2014). I estimate a 6.8% decline in investment price between 2005 and 2016 for eight countries using the method outlined by Karabarbounis and Neiman (2014). Next, after I account for all observed parameter changes, I infer the necessary expansion of automatable tasks (product innovation) that should have taken place to account for changes in labor market outcomes. Even with no appropriate proxy for the effect of product innovation, information on technology advancement from automation of routine tasks to more complex tasks has been dominating discussions both in academic and policymaker circles. Now tasks that have been previously considered safe from automation, such as image and speech recognition, are being performed by computer algorithms. For example, algorithmic image classification has exceeded the human level of accuracy as of 2015 (machine error fell below 5%), and now its error rate is less than 1%(Perrault et al., 2019).

To unveil the contribution of each change in policy, costs, or technology, I calibrate the model to 2005 moments and then simulate changes in parameters associated with policy: replacement rates, bargaining power, employment protection. I associate a change in trade union density with parameter γ, workers' bargaining power. I relate a change in overall employment protection to the separation rate of L-type workers, δ_L.

Table 3: Observed changes in policy and price of automation

Data	Parameter	2005	2016	Source
Replacement rate	b_H	38%	34%	OECD
Trade Union Density	γ	35.6%	32.4%	OECD
Collective Bargaining Coverage	γ	61.03%	54.09%	OECD
Employment Protection Index	δ_L	1	0.9595	OECD (2005=1)
Relative investment price	ξ	1	0.9320	PWT (2005=1)

Table 4: Contribution of each channel to changes in education, employment rates and wage inequality

	Data	$\downarrow b_H$	...+ $\downarrow \gamma$	...+ $\uparrow \delta_L$	...+ $\downarrow \xi$	...+ $\uparrow \varphi$	...+ $\downarrow \alpha$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔE_L	2.938	2.772	5.895	4.382	6.966	9.092	6.727
ΔE_H	1.435	0.196	1.551	1.490	1.617	1.739	1.534
$\Delta\mu$	36.325	7.107	11.669	12.720	14.564	26.821	33.507
$\Delta w_H/w_L$	-9.335	-1.829	-1.833	-1.828	-1.803	-1.899	-0.160
ΔGDP	5.106	4.634	9.431	9.313	12.102	21.681	19.340

Notes: μ denotes share of tertiary educated, E_i is an employment rate of i-type worker, $i \in \{H, L\}$, δ_L is a separation rate of L worker.

Table 4 summarizes the simulation results. The first column of Table 4 shows percentage changes in labor market outcomes between 2005 and 2016 averaged across countries. The second column shows a simulated percentage change in outcomes with a change only in the replacement rate for H-type workers from 2005 to 2016. The following columns add one more observed change in a different parameter. For example, the Column 4 model includes changes in replacement rate, bargaining power, and separation rate.

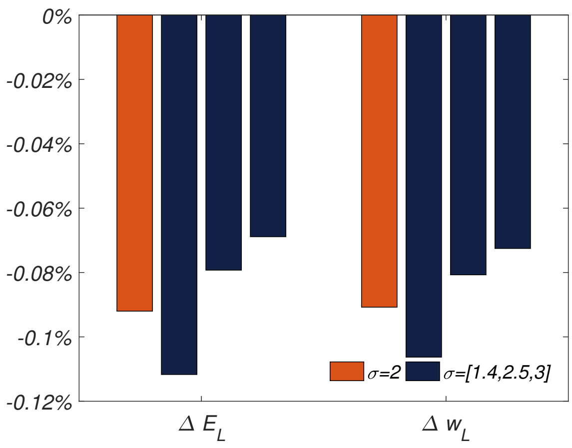
Institutional factors account for approximately one-third of changes in education, relative wages, and positive employment changes for both types of workers. Cumulatively, L-type workers' employment increases by 4.38% and employment of H-type workers by 1.49% in the model, and data show smaller increases but a similar pattern of a higher increase for L-type workers compared to H-type (2.94% vs. 1.44%). This is consistent with the idea that more flexibility in labor markets and less regulated are associated with higher employment.

However, by themselves, institutional factors could not account for changes in the education structure of the labor force. The model predicts a 12.7% increase in the share of workers with tertiary education, but in the data, this increase is 3 times higher (36%). A decrease in wage inequality predicted by the model is lower than the data (-1.8% vs. -9.3%). However, in the model, institutional changes have the opposite effect on individual wages. In the data (inflation-adjusted), wages have increased for both groups on average (11% and 1.3% for L- and H-type workers, respectively). However, the model predicts a decrease for both L- and H-type workers (-1.15% and -2.8%). Note that the model overestimates the growth in GDP per capita at the same time: +9.3% in the model vs. 5.11% in the data.

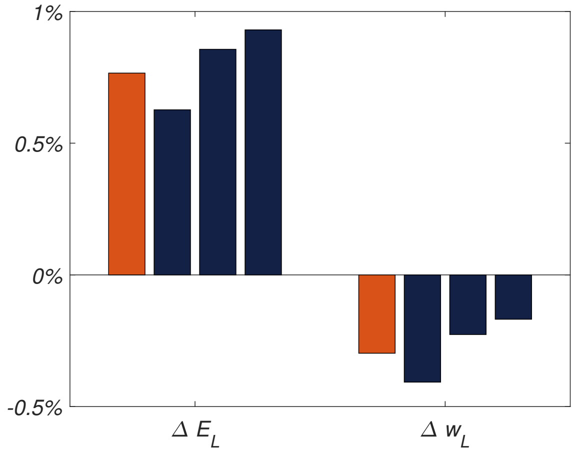
Next, I add a change in technological factors: a decline in automation price (ξ) and an increase in technology availability (φ). With a 6.8% decrease in automation price, all labor outcomes move in the same direction as with institutional changes: employment rates increase for both types of workers, GDP per capita increases, education share also increases, but only slightly from 12.5% to 14.56% which accounts 40% of an actual increase. Next, I could assume an expansion of automatable tasks since there is only anecdotal evidence on this process. If I assume an increase in technology availability (φ) from 2.77% (2005 calibrated value) to 4.15%, the model predicts that share of tertiary educated workers increases cumulatively by 26.8% (about 74% of actual), but the model grossly overestimates the increase in the employment rate of L-type workers and an increase in GDP per capita.

Another factor contributing to the change in education shares is a shift towards the H sector (services). It could be represented by a decline in the α parameter in the model (-10%). While this change in economic structure could account for the educational attainment growth, it leads to an increase in wage inequality between two groups of workers rather than the observed decrease.

To sum up, institutional factors could account for most of the improvement in employment rates of both types of workers, but only for one-third of the growth in educational attainment. As for technological factors, a decline in automation price could not explain the full magnitude of an education increase, thus, a significant product innovation may have occurred during the analyzed period. Overall, technological factors could explain a larger proportion of labor market changes.



(a) Expansion of capabilities (1% $\uparrow \varphi$)



(b) Decline in price of automation (1% $\downarrow \xi$)

Figure 5: Baseline model: elasticity of labor market responses to automation parameters (φ, ξ) increases in elasticity of substitution between H and L sectors

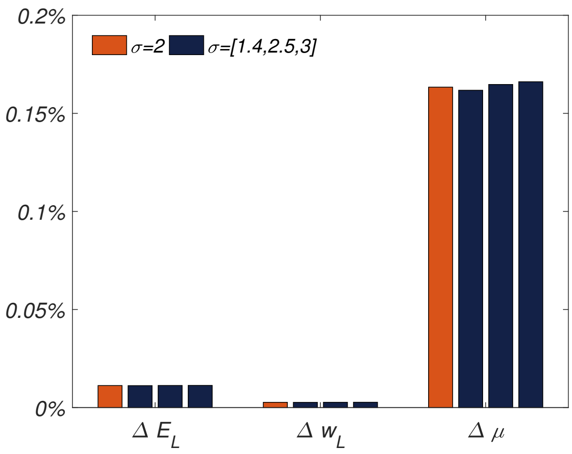
4.5 Robustness checks

To test the robustness of my results, I use different parametrizations for elasticity of substitution and search costs as well as individual country calibrations.

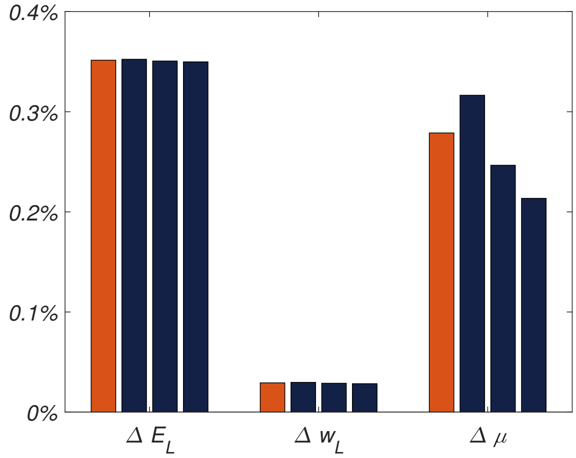
In the base calibration of my model, I use elasticity of substitution between intermediate sectors (H-type and L-type workers) equal to 2, $\sigma = 2$. To check the robustness of my results, I vary $\sigma \in \{1.4, 2.5, 3\}$ and repeat simulations for both models, with and without education adjustment. Results are documented in Table C6. Figure 5 compares responses of employment and wages of L-type workers in the baseline model across different elasticities. The orange bar shows the results for $\sigma = 2$, base calibration, and blue bars are for $\sigma \in \{1.4, 2.5, 3\}$. In the model without education adjustment, higher elasticity of substitution leads to a smaller magnitude of employment and wage responses to the expansion of capabilities ($\uparrow \varphi$). As for a decline in price of automation ($\downarrow \xi$), higher elasticity is associated with a larger employment response but a smaller wage response. Other labor outcomes change their elasticity to automation parameters in a similar manner (see Table C6).

In the model with the education adjustment, the different parametrization of σ mainly affects education investment, while employment and wages sensitivity stay similar to the base parametrization. Figure 6 shows the elasticity of employment, wages, and education with respect to technological change with different parametrization. When the elasticity of substitution is higher, education responds less to price declines, and its response is almost the same to a change in technology availability.

As for search costs, I set the ratio of search costs to workers' wages (κ_i / w_i) to 0.5 as a base parametrization. Here, I check whether changing this ratio to 0.1 and 0.9



(a) Expansion of capabilities (1% $\uparrow \varphi$).



(b) Decline in price of automation (1% $\downarrow \xi$).

Figure 6: Full model with education adjustment: education elasticity to a decline in price of automation becomes smaller as elasticity of substitution increases.

influences the results. Although Table C7 shows that those changes in the ratio lead to changes in some calibrated model parameters, the elasticity of labor market responses stays the same (see Table C8).

Additionally, I calibrate and simulate my model without educational adjustment for each country individually, and then I average the elasticity of responses across countries. The averages are reported in Table C5. The resulting elasticity of labor market outcomes to automation and policy parameters are similar to was reported in Table C1.

5 Conclusion and discussion

In this paper, I use a simple general equilibrium framework with skill heterogeneity and automation to evaluate the impact of automation on labor market outcomes. I distinguish between two characteristics of automation: prices and capabilities of automation. I show that these two characteristics of automation might have distinct effects on the labor market. When the capabilities of automation expand, there are more functions or tasks that could be automated. In general equilibrium, employment could increase or decrease, and this effect depends on the current labor market institutions, such as job protection or unemployment support. When the price of automation becomes more affordable without a change in its capabilities, it attracts more firms to enter the market, leading to a positive employment effect in equilibrium; however, this occurs at the cost of lower wages for workers.

In the model with the education adjustment, automation encourages workers to invest in education. Employment and wages of low-skill workers could actually increase in general equilibrium compared to the prediction of the model without adjustment. Another feature of the model with an educational adjustment is that the elasticity of labor outcomes to policy parameters increases compared to the model without such adjustment. Moreover, for some policy instruments, short-run impact is the opposite of the long-run impact. For example, unemployment benefits decrease inequality in the short-run but increase it in the long run by discouraging educational investment.

In the paper, I make two simplification assumptions that might affect the policy implications. The first assumption is that workers with tertiary education (H-types) are non-automatable. For future research, the model could be generalized to include the nonzero probability of automation, given the evidence on the recent technological developments.[15] However, as long as automation is more widespread for the L sector than for the H sector, I argue that results hold. Next, I do not explicitly model the educational subsidy as being included in the government budget constraint. Subsequently, incorporating it into the constraints might affect the financing of other policies, e.g., unemployment benefits.

[15]See Webb (2020)

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A Appendix A. Proofs

A.1 Wage determination

Wages in each sector is determined by the Nash bargaining. In sector H firm has no alternative to labor, thus its outside option is zero. Plugging in Eq.(2) and (5) into $(1-\gamma)(J_H^E - J_H^U) = \gamma J^H$ gives us equation (A1).

$$(1-\gamma)(w_H(1-\tau) - \rho J_H^U) = \gamma(p_H - w_H - \delta_H T) \tag{A1}$$

Solving it for wage w_H and substituting $(J_H^E - J_H^U) = \gamma/(1-\gamma)\kappa_H\theta_H$ in ρJ_H^U we arrive at Eq.(11).

In sector L, outside option is automation, thus, firms negotiates a wage accounting for foregone option to wait and automate.

$$(1-\gamma)\frac{w_L(1-\tau) - \rho J_L^U}{\rho + \delta_L} = \gamma\Big(\frac{p_L - w_L - \delta_L T}{\rho + \delta_L} - (\kappa_L - \phi J^M)\Big) \tag{A2}$$

Solving it for wage w_L and substituting $(J_L^E - J_L^U) = \gamma/(1-\gamma)\theta_L(\kappa_L - \varphi J^M)$ in ρJ_L^U we arrive at Eq.(12).

A.2 Price effects

Using equations (14), (17), (18), (15), find partial derivatives of p_H and p_L with respect to θ_L, θ_H and μ.

Effect on output. Using Eq. (17), (18), it is easy to show that $\partial Y_i/\partial\theta_j = 0$ and

$$\frac{\partial Y_L}{\partial \theta_L} = \frac{Y_L}{\theta_L(q_L+\varphi)}\Big(\varphi + f_L' u_L(1 - \frac{\theta_L\varphi}{\delta_L})\Big) > 0 \qquad \frac{\partial Y_L}{\partial \mu} = -\frac{Y_L}{(1-\mu)} < 0$$

$$\frac{\partial Y_H}{\partial \theta_H} = -\mu\frac{\partial u_H}{\partial \theta_H} > 0 \qquad \frac{\partial Y_H}{\partial \mu} = \frac{Y_H}{\mu} > 0$$

To prove that $\partial Y_L/\partial\theta_L > 0$, I show that $\varphi + f_L' u_L(1 - \frac{\theta_L\varphi}{\delta_L}) > 0$:

$$\varphi(1 - f_L' u_L\theta_L/\delta_L) > -f_L' u_L$$
$$\varphi > -\frac{f_L' u_L}{1 - f_L' u_L\theta_L/\delta_L}$$

$\varphi > 0$, while right-hand side of the equation above is below zero since

$$\begin{aligned} 1 - f_L' u_L \theta_L / \delta_L &> 0 \\ 1 &> f_L' \theta_L / (\delta_L + f_L) \\ 1 &> \underbrace{\frac{f_L' \theta_L}{f_L}}_{(1-\eta)} \frac{f_L}{\delta_L + f_L} \\ 1 &> (1-\eta)(1-u_L) \end{aligned}$$

Effect of output on prices. Next, partial derivatives of prices to intermediate sector outputs is given by

$$\partial p_L / \partial Y_L = -\sigma^{-1} \frac{p_L}{Y_L} \frac{p_H Y_H}{Y} < 0 \qquad \partial p_L / \partial Y_H = \sigma^{-1} \frac{p_L p_H}{Y} > 0$$

$$\partial p_H / \partial Y_H = -\sigma^{-1} \frac{p_H}{Y_H} \frac{p_L Y_L}{Y} < 0 \qquad \partial p_H / \partial Y_L = \sigma^{-1} \frac{p_L p_H}{Y} > 0$$

Effect of market tightness. Combining equation above, it is easy to sign the following expressions:

$$\frac{\partial p_L}{\partial \theta_L} = \frac{\partial p_L}{\partial Y_L} \frac{\partial Y_L}{\partial \theta_L} < 0 \qquad \frac{\partial p_L}{\partial \theta_H} = \frac{\partial p_L}{\partial Y_H} \frac{\partial Y_H}{\partial \theta_H} > 0$$

$$\frac{\partial p_H}{\partial \theta_H} = \frac{\partial p_H}{\partial Y_H} \frac{\partial Y_H}{\partial \theta_H} < 0 \qquad \frac{\partial p_H}{\partial \theta_L} = \frac{\partial p_H}{\partial Y_L} \frac{\partial Y_L}{\partial \theta_L} > 0$$

$$\frac{\partial p_L}{\partial \mu} = -Y_L \frac{\partial p_L}{\partial Y_L} \frac{1}{(1-\mu)\mu} > 0 \qquad \frac{\partial p_H}{\partial \mu} = Y_H \frac{\partial p_H}{\partial Y_H} \frac{1}{(1-\mu)\mu} < 0$$

Additionally, it is easy to show that $\frac{\partial p_H}{\partial \theta_H} = -\frac{Y_L}{Y_H} \frac{\partial p_L}{\partial \theta_H}$, $\frac{\partial p_L}{\partial \theta_L} = -\frac{Y_H}{Y_L} \frac{\partial p_H}{\partial \theta_L}$ and $\frac{\partial p_L}{\partial \mu} = -\frac{Y_H}{Y_L} \frac{\partial p_H}{\partial \mu}$.

A.3 Total derivatives, baseline model.

Plug wage equations into input demand equations (Eq. (7), (6)) to get job creation equations.

$$\kappa_H = \Omega_H \Big((1-\tau)(p_H - \delta_H T) - b_H \Big), \tag{A3}$$

$$\kappa_L = \Omega_L \Big((1-\tau)(p_L - \delta_L T) - b_L \Big) + \varphi J^M, \tag{A4}$$

where $\Omega_i = \frac{(1-\gamma)q_i}{(\rho+\delta_i)(1-\tau(1-\gamma))+\gamma f_i}$, $\partial \Omega_i / \partial \theta_i < 0$.

Let JC_L denote RHS of Eq.(A4) and JC_H denote RHS of Eq. (A3). Totally differentiate job creation conditions for both sectors and indifference condition (Eq. (19)).

$$d\kappa_H = \frac{\partial JC_H}{\partial \theta_H} d\theta_H + \frac{\partial JC_H}{\partial \theta_L} d\theta_L$$
$$d\kappa_L = \frac{\partial JC_L}{\partial \theta_H} d\theta_H + \frac{\partial JC_L}{\partial \theta_L} d\theta_L$$

Convert system of equations into a matrix form and to simplify future reference, let's denote each matrix entry by lower Latin letters:

$$\underbrace{\begin{pmatrix} \frac{\partial JC_H}{\partial \theta_H} & \frac{\partial JC_H}{\partial \theta_L} \\ \frac{\partial JC_L}{\partial \theta_H} & \frac{\partial JC_L}{\partial \theta_L} \end{pmatrix}}_{B} \begin{pmatrix} d\theta_H \\ d\theta_L \end{pmatrix} = \begin{pmatrix} a & b \\ d & e \end{pmatrix} \begin{pmatrix} d\theta_H \\ d\theta_L \end{pmatrix} = \begin{pmatrix} d\kappa_H \\ d\kappa_L \end{pmatrix}$$

$$\frac{\partial JC_H}{\partial \theta_H} = \Omega'_H \Big((1-\tau)(p_H - \delta_H T) - b_H \Big) + \Omega_H (1-\tau) \frac{\partial p_H}{\partial \theta_H} < 0$$
$$\frac{\partial JC_H}{\partial \theta_L} = \Omega_H (1-\tau) \frac{\partial p_H}{\partial \theta_L} > 0$$
$$\frac{\partial JC_L}{\partial \theta_H} = \Omega'_L \Big((1-\tau)(p_L - \delta_L T) - b_L \Big) + \Sigma_L (1-\tau) \frac{\partial p_L}{\partial \theta_L} < 0$$
$$\frac{\partial JC_L}{\partial \theta_H} = \Sigma_L \frac{\partial p_L}{\partial \theta_H} > 0$$

where$\Sigma_L = \Omega_L(1-\tau) + \varphi/(\rho + \delta_M) > 0$

The sign pattern in matrix B above is as follows:

$$\begin{pmatrix} - & + \\ + & - \end{pmatrix}$$

Inverse of matrix B is then

$$B^{-1} = \frac{1}{ae - bd} \begin{pmatrix} e & -b \\ -d & a \end{pmatrix},$$

where $a < 0, e < 0, b > 0, d > 0$, $ae - bd > 0$.

$$
\begin{aligned}
ae - bd = &\Big(\frac{\partial JC_H}{\partial \theta_H}\frac{\partial JC_L}{\partial \theta_L} - \frac{\partial JC_H}{\partial \theta_L}\frac{\partial JC_L}{\partial \theta_H}\Big) = \\
&[\Omega_H'((1-\tau)(p_H - \delta_H T) - b_H) + \Omega_H(1-\tau)\frac{\partial p_H}{\partial \theta_H}] \\
&\times [\Omega_L'((1-\tau)(p_L - \delta_L T) - b_L) + \underbrace{(\Omega_L(1-\tau) + \varphi/(\rho+\delta_M))}_{\Sigma_L}\frac{\partial p_L}{\theta_L}] \\
&- [\Omega_H(1-\tau)\frac{\partial p_H}{\partial \theta_L}][\Sigma_L \frac{\partial p_L}{\theta_H}] \\
&\text{(using } \partial p_i/\partial \theta i = -\partial p_j/\partial \theta_i Y_j/Y_i) \\
&= [\Omega_H'((1-\tau)(p_H - \delta_H T) - b_H)][\Omega_L'((1-\tau)(p_L - \delta_L T) - b_L)] + \\
&+ [\Omega_H'((1-\tau)(p_H - \delta_H T) - b_H)]\Sigma_L \frac{\partial p_L}{\theta_L} + (1-\tau)\Omega_L' \frac{\partial p_H}{\theta_H} > 0
\end{aligned}
$$

A.3.1 Changes in educational attainment

$$
\begin{pmatrix} d\theta_H/d\mu \\ d\theta_L/d\mu \end{pmatrix} = B^{-1}\begin{pmatrix} d\kappa_H/d\mu - \frac{\partial JC_H}{\partial \mu} \\ d\kappa_L/d\mu - \frac{\partial JC_L}{\partial \mu} \end{pmatrix} = B^{-1}\begin{pmatrix} 0 - c \\ 0 - f \end{pmatrix} = \frac{1}{ae - bd}\begin{pmatrix} -ce + bf \\ cd - af \end{pmatrix},
$$

where $\partial JC_H/\partial \mu < 0$, $\partial JC_L/\partial \mu > 0$.

$$
\begin{aligned}
bf - ce &= \Omega_H(1-\tau)\frac{\partial p_H}{\partial \theta_L}\Sigma_L \frac{\partial p_L}{\partial \mu} - \Big(\Omega_L'((1-\tau)(p_L - \delta_L T) - b_L) + \Sigma_L \frac{\partial p_L}{\partial \theta_L}\Big)\Omega_H(1-\tau)\frac{\partial p_H}{\partial \mu} \\
&= \frac{\partial p_H}{\partial \theta_L}\Sigma_L \frac{\partial p_L}{\partial \mu} - \Sigma_L \frac{\partial p_L}{\partial \theta_L}\frac{\partial p_H}{\partial \mu} - \Omega_L'((1-\tau)(p_L - \delta_L T) - b_L)\frac{\partial p_H}{\partial \mu} < 0
\end{aligned}
$$

$$
\begin{aligned}
af - cd &= [\Omega_H'((1-\tau)(p_H - \delta_H T) - b_H) + \Omega_H(1-\tau)\frac{\partial p_H}{\partial \theta_H}]\Sigma_L \frac{\partial p_L}{\partial \mu} - \Sigma_L \frac{\partial p_L}{\partial \theta_H}\Omega_H(1-\tau)\frac{\partial p_H}{\partial \mu} \\
&= \Omega_H'/\Omega_H \Sigma_L((1-\tau)(p_H - \delta_H T) - b_H) < 0
\end{aligned}
$$

A.3.2 Proof of Proposition 1: Changes in technology availability

$$
\begin{pmatrix} d\theta_H/d\varphi \\ d\theta_L/d\varphi \end{pmatrix} = B^{-1}\begin{pmatrix} d\kappa_H/d\varphi - \frac{\partial JC_H}{\partial \varphi} \\ d\kappa_L/d\varphi - \frac{\partial JC_L}{\partial \varphi} \end{pmatrix} = \frac{1}{ae - bd}\begin{pmatrix} -e(\frac{\partial JC_H}{\partial \varphi}) + b(\frac{\partial JC_L}{\partial \varphi}) \\ d(\frac{\partial JC_H}{\partial \varphi}) - a(\frac{\partial JC_L}{\partial \varphi}) \end{pmatrix},
$$

where $\partial JC_H/\partial \varphi > 0$, $\partial JC_L/\partial \varphi = \Sigma_L \frac{\partial p_L}{\partial \varphi} + J^M > 0$ iff $\frac{\partial p_L}{\partial \varphi} > -J^M/\Sigma_L$.

Independent of whether $\partial JC_L/\partial \varphi > 0$, market tightness in H sector is increasing in technology availability:

$$\begin{aligned} d\theta_H/d\varphi &= -[\Omega_L'((1-\tau)(p_L-\delta_L T)-b_L)+\Sigma_L\frac{\partial p_L}{\partial\theta_L}]\Omega_H(1-\tau)\frac{\partial p_H}{\partial\varphi} \\ &\quad +[\Sigma_L\frac{\partial p_L}{\partial\varphi}+J^M]\Omega_H(1-\tau)\frac{\partial p_H}{\partial\theta_L} \\ &= -\Omega_L'((1-\tau)(p_L-\delta_L T)-b_L)\Omega_H\frac{\partial p_H}{\partial\varphi}+J^M\Omega_H(1-\tau)\frac{\partial p_H}{\partial\theta_L} > 0 \end{aligned}$$

If $\partial JC_L/\partial\varphi > 0$, then

$$\begin{aligned} d\theta_L/d\varphi &= \Sigma_L\frac{\partial p_L}{\partial\theta_H}\Omega_H(1-\tau)\frac{\partial p_H}{\partial\varphi}-[\Omega_H'((1-\tau)(p_H-\delta_H T)-b_H) \\ &\quad +\Omega_H(1-\tau)\frac{\partial p_H}{\partial\theta_H}][\Sigma_L\frac{\partial p_L}{\partial\varphi}+J^M] \\ &= -\Omega_H'((1-\tau)(p_H-\delta_H T)-b_H)[\Sigma_L\frac{\partial p_L}{\partial\varphi}+J^M]-\Omega_H(1-\tau)\frac{\partial p_H}{\partial\theta_H}J^M > 0 \end{aligned}$$

If $\partial JC_L/\partial\varphi < 0$, then

$d\theta_L/d\varphi > 0$ if and only if

$$-\Omega_H'((1-\tau)(p_H-\delta_H T)-b_H)[\Sigma_L\frac{\partial p_L}{\partial\varphi}+J^M] > \Omega_H(1-\tau)\frac{\partial p_H}{\partial\theta_H}J^M$$

A.3.3 Proof of Proposition 1: Changes in automation price

No price effects for both sectors: $\partial p_H/\partial\xi = \partial p_L/\partial\xi = 0$. Consequently, $\partial JC_H/\partial\xi = 0$ and $\partial JC_L/\partial\xi = -\varphi/(\rho+\delta_M)$

$$\begin{pmatrix} d\theta_H/d\xi \\ d\theta_L/d\xi \end{pmatrix} = B^{-1}\begin{pmatrix} -\frac{\partial JC_H}{\partial\xi} \\ -\frac{\partial JC_L}{\partial\xi} \end{pmatrix} = \frac{1}{ae-bd}\begin{pmatrix} -b\varphi/(\rho+\delta_M) \\ a\varphi/(\rho+\delta_M) \end{pmatrix}$$

where $d\theta_H/d\xi < 0$, $d\theta_L/d\xi < 0$.

A.3.4 Proof of Proposition 2: Changes in wage of H-types, w_H

$$\begin{aligned} \frac{dw_H}{d\xi} &= \gamma\Big(\frac{dp_H}{d\xi}+\frac{d\theta_H}{d\xi}\kappa_H\Big) \\ \frac{dw_H}{d\xi} &> 0 \text{ iff } \frac{dp_H}{d\xi} > -\frac{d\theta_H}{d\xi}\kappa_H, \end{aligned}$$

where $d\theta_H/d\xi < 0$, which implies that $\frac{dp_H}{d\xi}$ should be positive.

$$\frac{dp_H}{d\xi} = \sigma^{-1}\frac{p_H p_L}{Y}\Big(- \frac{Y_L}{Y_H}\frac{\partial Y_H}{\partial \theta_H}\frac{d\theta_H}{d\xi} + \frac{\partial Y_L}{\partial \theta_L}\frac{d\theta_L}{d\xi}\Big)$$
$$\frac{dp_H}{d\xi} > 0 \text{ iff } \frac{Y_L}{Y_H}\frac{\partial Y_H}{\partial \theta_H}\frac{d\theta_H}{d\xi} < \frac{\partial Y_L}{\partial \theta_L}\frac{d\theta_L}{d\xi}$$
$$\text{(or in elasticities)}$$
$$\text{iff } \epsilon^{Y_L}_{\theta_L}\epsilon^{\theta_L}_{\xi} > \epsilon^{Y_H}_{\theta_H}\epsilon^{\theta_H}_{\xi},$$

where ϵ^i_j denotes elasticity of i with respect to j.

Condition for a positive wage change could also be re-written in elasticity terms

$$\frac{dw_H}{d\xi} > 0 \text{ iff } \frac{dp_H}{d\xi} > -\frac{d\theta_H}{d\xi}\kappa_H$$
$$\text{iff } \epsilon^{p_H}_{\xi} > -\frac{\kappa_H\theta_H}{p_H}\epsilon^{\theta_H}_{\xi}$$

Similarly, wage increases in technology availability if

$$\frac{dw_H}{d\varphi} > 0 \qquad \text{iff } \epsilon^{p_H}_{\varphi} > -\frac{\kappa_H\theta_H}{p_H}\epsilon^{\theta_H}_{\varphi}$$

A.3.5 Proof of Proposition 2: Changes in wage of L-types, w_L

$$\frac{dw_L}{d\xi} = \gamma\Big(\frac{dp_L}{d\xi}(1 - \frac{\varphi\theta_L}{\rho+\delta_M}) + \frac{\varphi\theta_L}{\rho+\delta_M} + \frac{d\theta_L}{d\xi}(\kappa_L - \varphi J^M)\Big)$$
$$\frac{dw_L}{d\xi} > 0 \text{ iff } \frac{dp_L}{d\xi}(1 - \frac{\varphi\theta_L}{\rho+\delta_M}) + \frac{\varphi\theta_L}{\rho+\delta_M} > -\frac{d\theta_L}{d\xi}(\kappa_L - \varphi J^M),$$

where $d\theta_L/d\xi < 0$, which implies that $\frac{dp_L}{d\xi}(1 - \frac{\varphi\theta_L}{\rho+\delta_M}) + \frac{\varphi\theta_L}{\rho+\delta_M}$ should be positive.

$$\frac{dp_L}{d\xi}(1 - \frac{\varphi\theta_L}{\rho+\delta_M}) + \frac{\varphi\theta_L}{\rho+\delta_M} > 0 \text{ iff } \frac{dp_L}{d\xi} > \frac{\varphi\theta_L}{\varphi\theta_L - \rho - \delta_M} > 1$$
$$\text{(or in elasticities)}$$
$$\text{iff } \epsilon^{p_L}_{\xi} > \frac{\xi}{p_L}\frac{\varphi\theta_L}{\varphi\theta_L - \rho - \delta_M},$$

where ϵ^i_j denotes elasticity of i with respect to j.

Similarly, wage increases in technology availability if

$$\frac{dw_L}{d\varphi} > 0 \qquad \text{iff iff } \frac{dp_L}{d\varphi}(1 - \frac{\varphi\theta_L}{\rho+\delta_M}) > -\frac{d\theta_L}{d\varphi}(\kappa_L - \varphi J^M) + \theta_L J^M$$

A.4 Total derivatives, full model.

Let JC_L denote RHS of Eq.(A4) and JC_H denote RHS of Eq. (A3). Totally differentiate job creation conditions and indifference condition (Eq. (19)).

$$
\begin{aligned}
d\kappa_H &= \frac{\partial JC_H}{\partial \theta_H} d\theta_H + \frac{\partial JC_H}{\partial \theta_L} d\theta_L + \frac{\partial JC_H}{\partial \mu} d\mu \\
d\kappa_L &= \frac{\partial JC_L}{\partial \theta_H} d\theta_H + \frac{\partial JC_L}{\partial \theta_L} d\theta_L + \frac{\partial JC_L}{\partial \mu} d\mu \\
dc &= \frac{\gamma}{1-\gamma} (\kappa_H + \frac{\partial p_L}{\partial \theta_H} \frac{\varphi \theta_L}{\rho + \delta_M}) d\theta_H - \frac{\gamma}{1-\gamma} (\kappa_L - \varphi J^M - \frac{\partial p_L}{\partial \theta_L} \frac{\varphi \theta_L}{\rho + \delta_M}) d\theta_L + 0 d\mu
\end{aligned}
$$

Convert system of equations into a matrix form and to simplify future reference, let's denote each matrix entry by lower Latin letters:

$$
\underbrace{\begin{pmatrix} \frac{\partial JC_H}{\partial \theta_H} & \frac{\partial JC_H}{\partial \theta_L} & \frac{\partial JC_H}{\partial \mu} \\ \frac{\partial JC_L}{\partial \theta_H} & \frac{\partial JC_L}{\partial \theta_L} & \frac{\partial JC_L}{\partial \mu} \\ \frac{\gamma}{(1-\gamma)} \left(\kappa_H + \frac{\varphi \theta_L}{\rho + \delta_M} \frac{\partial p_L}{\partial \theta_H} \right) & -\frac{\gamma}{(1-\gamma)} \left(\kappa_L - \varphi J^M - \frac{\varphi \theta_L}{(\rho + \delta_M)} \frac{\partial p_L}{\partial \theta_L} \right) & 0 \end{pmatrix}}_{A} \begin{pmatrix} d\theta_H \\ d\theta_L \\ d\mu \end{pmatrix} = \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & k \end{pmatrix} \begin{pmatrix} d\theta_H \\ d\theta_L \\ d\mu \end{pmatrix}
$$

$$
\frac{\partial JC_H}{\partial \mu} = \Omega_H (1-\tau) \frac{\partial p_H}{\partial \mu} < 0 \qquad \frac{\partial JC_L}{\partial \mu} = \Sigma_L \frac{\partial p_L}{\partial \mu} > 0
$$

where $\Sigma_L = \Omega_L(1-\tau) + \varphi/(\rho + \delta_M) > 0$

The sign pattern in matrix A above is as follows:

$$
\begin{pmatrix} - & + & - \\ + & - & + \\ + & - & 0 \end{pmatrix}
$$

Find the sign of the matrix A determinant could positive or negative depending on the parameters:

$$
\begin{aligned}
det A =& g(bf - ce) + h(af - cd) \\
bf - ce =& -\Omega_L' \Big((1-\tau)(p_L - \delta_L T) - b_L \Big) \Omega_H (1-\tau) \frac{\partial p_H}{\partial \mu} < 0 \\
af - cd =& \Omega_H' \Big((1-\tau)(p_H - \delta_H T) - b_H \Big) \Sigma_L \frac{\partial p_L}{\partial \mu} < 0 \\
& det A > 0 \text{ iff } g(bf - ce) > -h(af - cd)
\end{aligned}
$$

Inverse of matrix A is then

$$
A^{-1} = \frac{1}{det A} \begin{pmatrix} (ek - fh) & -(bk - ch) & bf - ce \\ -(dk - fg) & ak - cg & -(af - cd) \\ dh - eg & -(ah - bg) & ae - bd \end{pmatrix} = \begin{pmatrix} + & + & - \\ + & + & + \\ ? & ? & + \end{pmatrix}
$$

A.4.1 Impact of educational cost

System of equation to solve:

$$\begin{pmatrix} \frac{d\theta_H}{dc} \\ \frac{d\theta_L}{dc} \\ \frac{d\mu}{dc} \end{pmatrix} = A^{-1} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

Solve system:

$$\begin{aligned} \frac{d\theta_H}{dc} &= \frac{1}{detA}(bf - ce) > 0 \text{ iff } detA < 0 \\ \frac{d\theta_L}{dc} &= -\frac{1}{detA}(af - cd) < 0 \text{ iff } detA < 0 \\ \frac{d\mu}{dc} &= \frac{1}{detA}(ae - bd) < 0 \text{ iff } detA < 0 \end{aligned}$$

B Appendix B. Data sources

Educational attainment. I use a share of tertiary educated in population aged 25-64 averaged across 1999-2018 period for each country from ILO.

Employment rates. I obtain employment rates for 1999-2018 period for each country from ILO. Employment rates are provided for three educational levels: primary, secondary and tertiary. I calculate employment level for below tertiary education as a weighted average of employment level for secondary and primary education levels:

$$E_L = (E_p * share_p + E_s * share_s)/(share_p + share_s),$$

where $share_p$ and $share_s$ are share of population with primary and secondary education respectively.

Relative wages. Relative wages are calculated for each country country for 2005-2016 period using individual-level data from the Survey of Income and Living Conditions (SILC). Only employed workers of age between 25 and 64 are included in calculation. I use cash and noncash income

Labor share. Using EUKLEMS data for 1995-2017 (Adarov and Stehrer, 2019; Stehrer et al., 2019), I calculate labor share as labor costs (LAB) to value added (VA) ratio.

GDP. I divide real GDP in chained PPP USD (2011 constant dollars) by the number of engaged persons, both indicators are from the Penn World Tables version 9.1 (Feenstra et al., 2015). Then, I calculate GDP per employee relative to the average level.

Separation rates. Using average tenure from the OECD.Stat, I calculate the quarterly separation rate (δ) for each country as $0.25/tenure$. Then I use the ratio of separation rates () for high-skill and low-skill workers reported in Chassamboulli and Palivos (2014) as well as share of tertiary educated to approximate separation rates for each education level in each country. Separation rates solve this system of equations:

$$\begin{cases} \delta_H \mu + \delta_L (1-\mu) = \delta \\ \delta_H / \delta_L = ratio \end{cases}$$

Severance pay data. For the same set of countries, I use data on severance pay from the European Restructuring Monitor database on related legislation[16]. If severance pay is conditional on tenure, I use average tenure in the country from the OECD to determine what pay level to use. For example, in France employees are entitled to 25% of the gross monthly salary times years of seniority if their tenure is up to 10 years and 33.33% for tenure 11 years and more. Average tenure in France is 10.38 years, hence I use 25% times tenure divided by 12 months (0.25*10.38/12) to convert

[16] https://www.eurofound.europa.eu/observatories/emcc/erm/legislation

into relative monthly terms. For Finland there is no severance pay regulation. I then calculate average burden for all countries which is 235% of annual pay.

Replacement rate. I use the net replacement rate (NRR) from OECD WISE database averaged across all available years for each country.

The summary of the country parameters and average are shown in Table B1

Table B1: Country moments

	μ	E_H	E_L	w_H/w_L	Labor share	GDP	δ_H	δ_L	Severance ratio (T)	Replacement rate
Denmark	0.334	0.864	0.743	1.496	0.658	1.008	0.022	0.039	0.417	0.570
Finland	0.378	0.846	0.694	1.896	0.661	1.042	0.018	0.033	0.235	0.465
France	0.287	0.838	0.668	1.890	0.681	1.089	0.015	0.027	0.223	0.501
Hungary	0.197	0.818	0.628	2.395	0.598	0.634	0.018	0.032	0.250	0.213
Luxembourg	0.316	0.847	0.672	2.199	0.576	1.550	0.016	0.029	0.167	0.299
Netherlands	0.310	0.870	0.715	1.894	0.679	1.071	0.017	0.030	0.265	0.428
Poland	0.211	0.851	0.616	2.616	0.576	0.612	0.015	0.027	0.167	0.223
United Kingdom	0.350	0.865	0.728	1.943	0.644	0.993	0.020	0.037	0.155	0.296
Average	0.298	0.850	0.683	2.041	0.634	1.000	0.018	0.032	0.235	0.374

Notes: μ denotes share of tertiary educated, E_i is an employment rate of i-type worker, $i \in \{H, L\}$, δ_i is a separation rate of i worker.

C Appendix C. Additional figures and tables

C.1 Sensitivity to automation and policy parameters, base calibration

The following tables report results of simulations for both models, one with (full model) and one without educational adjustment (baseline model). See text for the description of calibration procedure.

Table C1: Sensitivity to 1% changes: baseline model

	ΔE_L	ΔE_H	$\Delta E_H/E_L$	Δw_L	Δw_H	$\Delta w_H/w_L$	Δls	ΔW	ΔW_L	ΔW_H
Technology parameters										
$\Delta\phi$	-0.092	0.004	0.096	-0.091	0.079	0.170	-0.119	-0.045	-0.151	0.064
$-\Delta\xi$	0.766	0.080	-0.681	-0.298	0.522	0.822	-0.551	0.537	0.282	0.800
Policy parameters										
ΔT	0.000	0.001	0.000	-0.009	-0.003	0.006	-0.006	0.000	-0.003	0.004
Δb_L	-0.084	-0.023	0.061	0.177	-0.043	-0.219	0.116	0.011	0.192	-0.175
$-\Delta\delta_L$	0.407	0.016	-0.390	0.071	0.003	-0.068	0.061	0.236	0.358	0.111
$\Delta\gamma$	-0.220	-0.186	0.034	0.383	0.018	-0.364	0.367	-0.008	0.174	-0.196

Note: ΔE_i denotes a percentage change in employment rate for workers of category $i \in \{H, L\}$, Δw_i denotes a percentage change in wages for both categories, ΔW_i is a welfare change, Δls is a labor share change.

Table C2: Sensitivity to 1% changes: full model

	ΔE_L	ΔE_H	$\Delta E_H/E_L$	Δw_L	Δw_H	$\Delta w_H/w_L$	Δls	ΔW	ΔW_L	ΔW_H	$\Delta\mu$
Technology parameters											
$\Delta\phi$	0.011	0.001	-0.010	0.003	-0.003	-0.005	-0.058	0.057	0.017	0.007	0.163
$-\Delta\xi$	0.351	0.018	-0.332	0.029	0.023	-0.006	-0.066	0.292	0.292	0.136	0.279
Policy parameters											
ΔT	0.003	0.001	-0.002	-0.004	-0.006	-0.001	-0.007	0.006	0.004	0.002	0.013
Δb_L	-0.271	-0.018	0.253	-0.059	0.121	0.179	0.124	-0.308	-0.188	-0.071	-0.642
$-\Delta\delta_L$	0.398	0.017	-0.380	0.031	0.024	-0.007	0.096	0.175	0.308	0.126	-0.157
$\Delta\gamma$	-0.463	-0.182	0.282	0.144	0.198	0.055	0.297	-0.340	-0.249	-0.088	-0.617
$-\Delta c$	0.287	-0.011	-0.297	0.514	-0.319	-0.829	0.068	0.649	0.744	-0.225	1.394

Table C3: Change in investment prices and educational attainment by decade

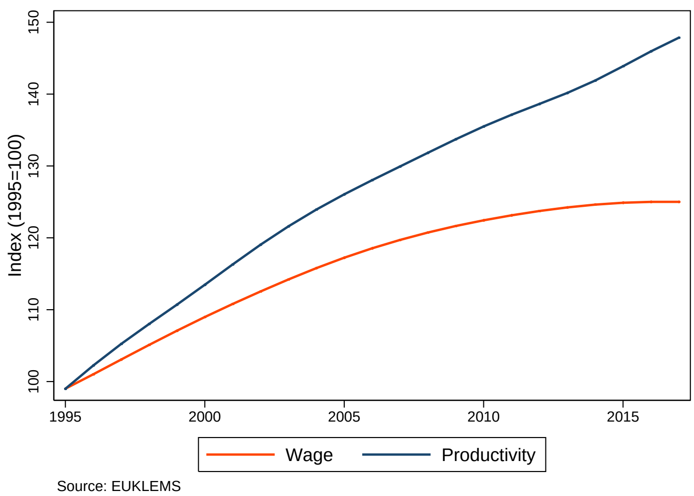
PWT: Change in log price*100				
	All	Europe	West EU	East EU
1980-1990	-18.8%	-17.4%	-19.7%	-14.1%
1990-2000	-15.4%	-8.5%	-3.7%	-51.1%
2000-2010	-12.9%	-22.4%	-22.3%	-20.6%
2010-2017	-2.2%	4.5%	4.7%	3.9%

Notes: Changes in both variables are obtain following the methodology in Karabarbounis and Neiman (2014) and using data from Penn World Tables.

C.2 Productivity vs wages growth

Using EUKLEMS data, I calculate output (GO) per hour worked (H_EMPE) and hourly compensation (COMP/H_EMPE) for several European countries. Gross output and compensation are both adjusted by value-added index (VA_PI). Series are smoothed using a lowess curve.

Figure C1 shows the well-document fact about the divergence of productivity and wage growth rates. Between 1995 and 2017 productivity per hour worked has increased by more than 45%, while wage has grown only by approximately 25%.



$$Productivity = \frac{\text{Gross Output}}{\text{Total hours worked}}$$

$$Wage = \frac{\text{Compensation}}{\text{Total hours worked}}$$

List of countries: Denmark, Finland, France, Luxembourg, Netherlands, UK

Figure C1: Wage growth is behind productivity growth

Figures C2 and C3 show growth in indices for individual countries. Those figures also illustrate different experiences across countries. In the UK and Luxembourg wage growth exceeded the growth in productivity, while other countries mostly show the opposite trend.

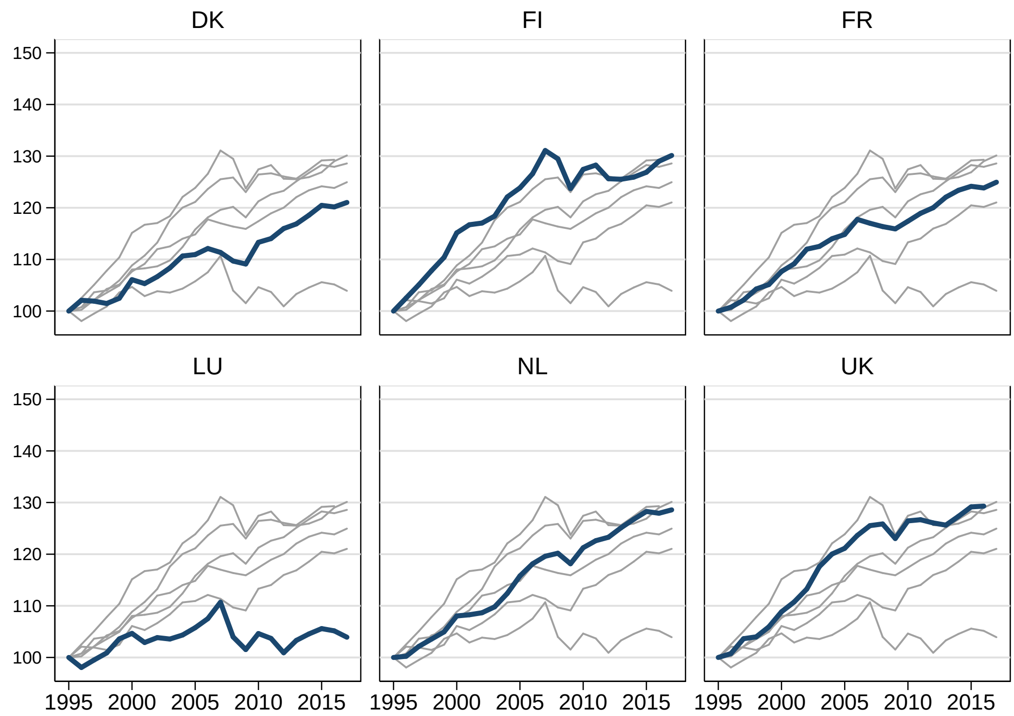


Figure C2: Labor productivity indices by country (output per hour worked)

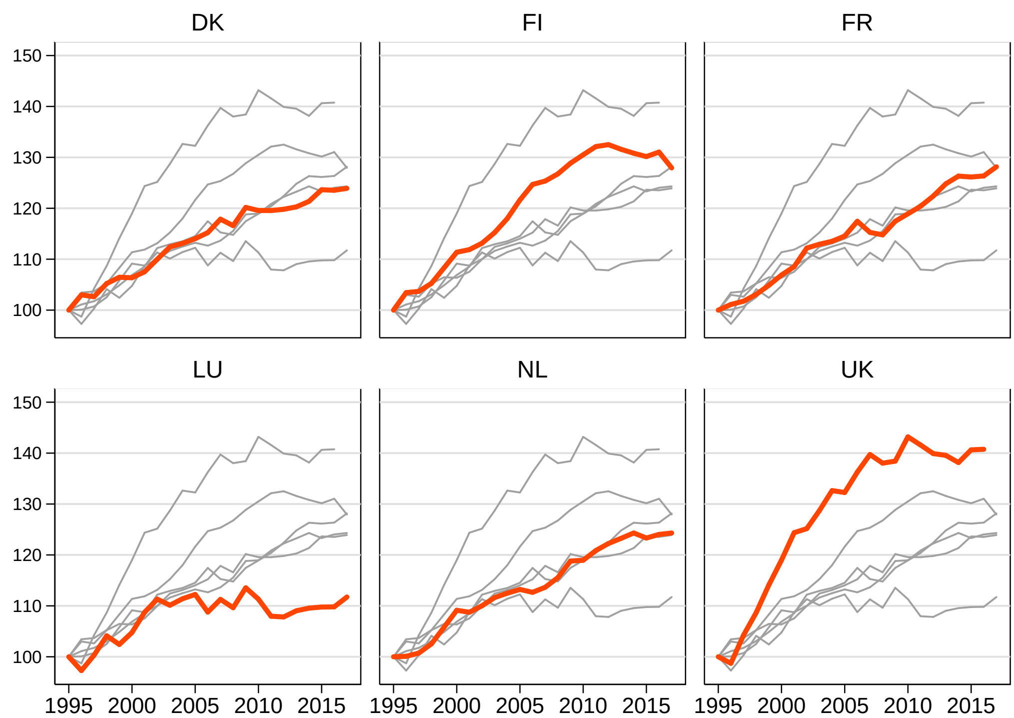


Figure C3: Hourly wages indices by country

C.3 Calibrated parameters for the full model

Table C4 compares calibrated parameters for the full and baseline models. The baseline model is a model with fixed educational shares, the full model is a model with endogenous education. To match moments in the baseline model, technological availability φ and the importance of L sector are higher compared to the model with endogenous education.

Table C4: Compare calibrated parameters in two models

Parameter	Baseline	Full
χ_L	0.079	0.084
χ_H	0.111	0.111
α	0.368	0.256
ϕ	0.106	0.027
A	1.188	1.389
c		0.568

C.4 Baseline model: average sensitivity to 1% change in parameters

Table C5 shows the average sensitivity across countries to changes in parameters in the baseline model (no education). Each cell in the table is an average of eight simulations, one for each country.

Table C5: Average sensitivity by country: baseline model

	ΔE_L	ΔE_H	$\Delta E_H/E_L$	Δw_L	Δw_H	$\Delta w_H/w_L$	Δls	ΔW	ΔW_L	ΔW_H
$\Delta\phi$	−0.091	0.003	0.094	−0.085	0.077	0.162	−0.115	−0.045	−0.145	0.059
$-\Delta\xi$	0.774	0.095	−0.674	−0.322	0.538	0.862	−0.581	0.545	0.265	0.841
ΔT	0.001	0.001	0.000	−0.009	−0.003	0.006	−0.007	0.000	−0.003	0.004
Δb_L	−0.094	−0.030	0.064	0.183	−0.048	−0.231	0.127	0.004	0.187	−0.191
$-\Delta\delta_L$	0.413	0.020	−0.392	0.068	0.004	−0.063	0.060	0.245	0.366	0.116
$-\Delta\gamma$	−0.225	−0.189	0.035	0.382	0.021	−0.360	0.370	−0.010	0.165	−0.195

C.5 Sensitivity to elasticity of substitution parameter, σ

Table C6: Varying elasticity σ: baseline model

	ΔE_L	ΔE_H	$\Delta E_H/E_L$	Δw_L	Δw_H	$\Delta w_H/w_L$	Δls	ΔW	ΔW_L	ΔW_H
Base calibration $\sigma = 2$										
$\Delta\phi$	-0.092	0.004	0.096	-0.091	0.079	0.170	-0.119	-0.045	-0.151	0.064
$-\Delta\xi$	0.766	0.080	-0.681	-0.298	0.522	0.822	-0.551	0.537	0.282	0.800
ΔT	0.000	0.001	0.000	-0.009	-0.003	0.006	-0.006	0.000	-0.003	0.004
Δb_L	-0.084	-0.023	0.061	0.177	-0.043	-0.219	0.116	0.011	0.192	-0.175
$-\Delta\delta_L$	0.407	0.016	-0.390	0.071	0.003	-0.068	0.061	0.236	0.358	0.111
$\Delta\gamma$	-0.220	-0.186	0.034	0.383	0.018	-0.364	0.367	-0.008	0.174	-0.196
$\sigma = 1.4$										
$\Delta\phi$	-0.112	0.004	0.116	-0.106	0.092	0.198	-0.100	-0.056	-0.180	0.072
$-\Delta\xi$	0.627	0.083	-0.540	-0.407	0.610	1.021	-0.412	0.463	0.078	0.860
ΔT	0.000	0.001	0.000	-0.009	-0.003	0.006	-0.006	0.000	-0.003	0.004
Δb_L	-0.070	-0.023	0.047	0.188	-0.052	-0.239	0.102	0.018	0.212	-0.182
$-\Delta\delta_L$	0.404	0.016	-0.386	0.068	0.005	-0.063	0.065	0.234	0.353	0.112
$\Delta\gamma$	-0.192	-0.186	0.005	0.406	-0.000	-0.404	0.339	0.006	0.215	-0.209
$\sigma = 2.5$										
$\Delta\phi$	-0.079	0.004	0.083	-0.081	0.071	0.152	-0.132	-0.039	-0.132	0.058
$-\Delta\xi$	0.856	0.078	-0.772	-0.226	0.465	0.693	-0.641	0.584	0.414	0.760
ΔT	0.000	0.001	0.000	-0.009	-0.003	0.006	-0.006	0.000	-0.003	0.004
Δb_L	-0.093	-0.022	0.071	0.169	-0.037	-0.206	0.125	0.006	0.178	-0.171
$-\Delta\delta_L$	0.410	0.016	-0.392	0.072	0.001	-0.071	0.059	0.237	0.361	0.110
$\Delta\gamma$	-0.239	-0.185	0.053	0.369	0.029	-0.338	0.385	-0.018	0.147	-0.188
$\sigma = 3$										
$\Delta\phi$	-0.069	0.003	0.072	-0.073	0.064	0.137	-0.142	-0.033	-0.117	0.053
$-\Delta\xi$	0.930	0.077	-0.846	-0.168	0.419	0.588	-0.715	0.623	0.522	0.728
ΔT	0.000	0.001	0.000	-0.009	-0.003	0.006	-0.006	0.000	-0.003	0.004
Δb_L	-0.101	-0.022	0.078	0.163	-0.032	-0.195	0.132	0.002	0.167	-0.168
$-\Delta\delta_L$	0.411	0.016	-0.394	0.074	0.000	-0.074	0.057	0.238	0.364	0.109
$\Delta\gamma$	-0.254	-0.185	0.069	0.357	0.039	-0.317	0.399	-0.026	0.125	-0.182

C.6 Sensitivity to search cost parameter, κ_i

Table C7: Sensitivity to search cost κ_i parametrization: a change in calibrated parameters in baseline model

	$\kappa_i/w_i = 0.5$	$\kappa_i/w_i = 0.1$	$\kappa_i/w_i = 0.9$
χ_L	0.079	0.035	0.106
χ_H	0.111	0.050	0.149
α	0.368	0.368	0.368
ϕ	0.106	0.021	0.191
A	1.188	1.188	1.188

Table C8: Sensitivity to search cost κ_i: no changes in elasticity of labor market outcomes in the baseline model

	ΔE_L	ΔE_H	$\Delta E_H/E_L$	Δw_L	Δw_H	$\Delta w_H/w_L$	Δls	ΔW	ΔW_L	ΔW_H
Base calibration $\kappa_i/w_i = 0.5$										
$\Delta\phi$	-0.092	0.004	0.096	-0.091	0.079	0.170	-0.119	-0.045	-0.151	0.064
$-\Delta\xi$	0.766	0.080	-0.681	-0.298	0.522	0.822	-0.551	0.537	0.282	0.800
ΔT	0.000	0.001	0.000	-0.009	-0.003	0.006	-0.006	0.000	-0.003	0.004
Δb_L	-0.084	-0.023	0.061	0.177	-0.043	-0.219	0.116	0.011	0.192	-0.175
$-\Delta\delta_L$	0.407	0.016	-0.390	0.071	0.003	-0.068	0.061	0.236	0.358	0.111
$\Delta\gamma$	-0.220	-0.186	0.034	0.383	0.018	-0.364	0.367	-0.008	0.174	-0.196
$\kappa_i/w_i = 0.1$										
$\Delta\phi$	-0.092	0.004	0.096	-0.091	0.079	0.170	-0.119	-0.045	-0.151	0.064
$-\Delta\xi$	0.766	0.080	-0.681	-0.298	0.522	0.822	-0.551	0.537	0.282	0.800
ΔT	0.000	0.001	0.000	-0.009	-0.003	0.006	-0.006	0.000	-0.003	0.004
Δb_L	-0.084	-0.023	0.061	0.177	-0.043	-0.219	0.116	0.011	0.192	-0.175
$-\Delta\delta_L$	0.407	0.016	-0.390	0.071	0.003	-0.068	0.061	0.236	0.358	0.111
$\Delta\gamma$	-0.220	-0.186	0.034	0.383	0.018	-0.364	0.367	-0.008	0.174	-0.196
$\kappa_i/w_i = 0.9$										
$\Delta\phi$	-0.092	0.004	0.096	-0.091	0.079	0.170	-0.119	-0.045	-0.151	0.064
$-\Delta\xi$	0.766	0.080	-0.681	-0.298	0.522	0.822	-0.551	0.537	0.282	0.800
ΔT	0.000	0.001	0.000	-0.009	-0.003	0.006	-0.006	0.000	-0.003	0.004
Δb_L	-0.084	-0.023	0.061	0.177	-0.043	-0.219	0.116	0.011	0.192	-0.175
$-\Delta\delta_L$	0.407	0.016	-0.390	0.071	0.003	-0.068	0.061	0.236	0.358	0.111
$\Delta\gamma$	-0.220	-0.186	0.034	0.383	0.018	-0.364	0.367	-0.008	0.174	-0.196