Automation, Offshoring and Employment Distribution in Western Europe *

Jocelyn Maillard §

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Abstract

This paper investigates the effects of automation and offshoring on the dynamics of the occupational distribution of employment with a focus on Western Europe between 2000 and 2016. I use a general equilibrium model with three regions, three types of workers, ICT capital, trade in final goods and endogenous offshoring. Fed with exogenous measures of ICT-capital prices and trade costs, the model replicates key features of the data. It matches the observed dynamics of offshoring to Eastern Europe and Asian countries. It also reproduces accurately the observed polarization of the labor market: abstract and manual labor increase while routine labor falls. A counterfactual experiment reveals that automation is the main driver of the polarization. Since it is also the only factor that drives individuals to become abstract (high-skill) workers, it is welfare enhancing. The effects of falling trade costs on labor polarization are smaller, but imply welfare gains.

Keywords: Automation, offshoring, labor-market polarization, European employment distribution

JEL Classification: F16, F41, J24, J62, O33

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§Univ Lyon, Université Lumière Lyon 2, GATE UMR 5824. 93, Chemin des Mouilles, F-69130 Ecully, France; e-mail: maillard@gate.cnrs.fr.

1 Introduction

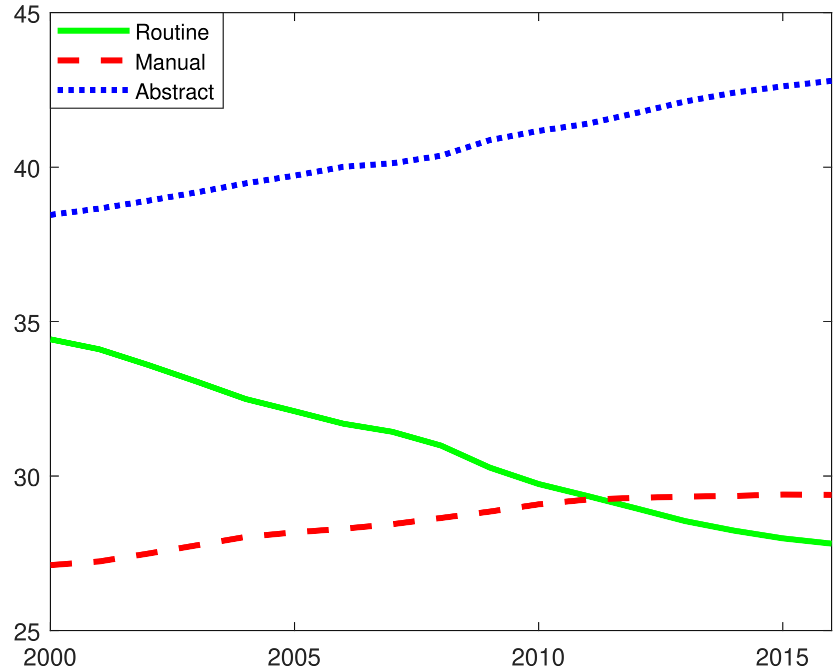
Since the 18th century, machines and trade have modified the occupational distribution of employment. With the Industrial Revolution, small workshops with low-productivity skilled craftsmen were replaced by large factories with machines operated by low-skill workers. Those changes brought fear of a strong and permanent increase in unemployment. For example, in England, high-skill textile workers started the Luddite movement at the beginning of the 19th century to protest against the excessive use of machines since they believed it would impoverish them. However, the increase in unemployment was only temporary. New jobs were created: supervisors to look after workers or mechanics to fix machines. Besides, this new labor organization led to a strong decrease in the cost of English textile. As such, the international demand for English textile strongly increased at the expense of Indian handcraft production. Thus, overall labor demand did not decrease at that time in England. However, it brought a disruption of the labor-market as several occupations disappeared while others were created (see Mokyr et al. (2015)). More technological progress occurred later, during the 20th century, with the inception of electricity or electronic goods for instance. Furthermore, trade strongly increased with the invention of planes, improvement of boats or the decrease in tariffs with the General Agreement on Tariffs and Trade after World War II. Arguably, they all had similar consequences on employment. Automation and trade mainly had short-term temporary effects on the aggregate demand for labor, but led to long-term structural changes regarding the types of skills that are required and the precise tasks that must be performed.

This paper investigates the respective effects of automation, and international trade on the occupational displacement of employment in Western Europe since 2000.[1] Over the recent period, automation has risen with the development of the Internet. Besides, Western European countries have increased their trade intensity after China joined WTO in 2001 or after Central and Eastern European countries entered the European Union in 2004 and 2007. Both automation and trade – through offshoring – have been argued to drive the polarization of employment observed since the end of the 20th century in the United States (see Autor et al. (2003), Autor and Dorn (2013), Acemoglu and Autor (2011)) and in Western European countries (see Goos et al. (2014)). Polarization can be defined as the joint increase in the number of high-skill workers – supplying abstract tasks – and of low-skill workers – delivering manual non-routine tasks – at the expense of middle-skill workers supplying routine tasks. Automation and trade contribute to this polarization as routine occupations can be easily performed by machines or offshored to be supplied by workers in other countries. Figure 1 depicts the actual labor-market polarization process for Western European countries between 2000 and 2016. We can see that the routine labor share of the non-agricultural labor force dropped by 6.6 percentage points while the abstract and routine labor shares respectively increased by 4.3 and 2.3 percentage points during the period.[2]

[1]From now on, when I use the notions of international trade or trade, it includes both offshoring and international trade on final goods.

[2]The separation of occupations between the three categories is explained in Appendix A.

Figure 1: Occupational changes in Western Europe



Shares are expressed in percentages of all workers but Armed Forces (ISCO classification 0) and Agricultural workers (6 and 92.). The countries included are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom.

I develop a three-region general equilibrium model with three types of workers. High-skill workers supply abstract labor and middle-skill workers provide routine labor to produce an internationally tradable good with Information and Communication Technology (ICT) capital. Low-skill workers supply manual labor to produce a non-tradable good. Individuals have to train to become either high or middle-skill workers but skills are randomly destroyed every period. Firms in Western European countries can offshore the production of routine tasks either to Central and Eastern European countries or to developing Asian countries. The amount of offshored labor depends on the relative wage and two costs: the trade cost and an "offshorability" cost that varies depending on the task. Furthermore, I follow the literature and assume that ICT capital and abstract labor are relative complements while ICT capital and routine labor are relative substitutes. The steady state of the model is carefully parametrized to replicate key characteristics of each of the three regions in 2000. I then subject the model to actual yearly exogenous processes for trade costs and ICT-capital prices. The model replicates accurately the increase in offshoring and the polarization of employment in Western European countries over the period. Using this reference path, I then conduct a counterfactual analysis where I feed the model with the exogenous processes separately to decompose the various factors explaining the dynamics of the occupational distribution of employment. Last, I look at the aggregate welfare consequences of those dynamics for Western Europe.

To begin with, the relevance of the model is validated by its ability to match almost perfectly the dynamics of offshoring for Western European firms. Moreover, the two driving forces replicate the job polarization process very well: the routine labor share falls from 34.4% to 28.4% of the non-agricultural labor share in the model while it drops from 34.4% to 27.8% in the data. The abstract labor share rises from 38.5% to 42.2% in the model while it reaches 42.8% in the data. The manual labor share increases from 27.1% to 29.4% both in the model and the data. The mechanisms run as follows. First, the decrease in the price of ICT capital leads to an increase in investment in ICT capital and thus of automation. It substitutes for routine labor. Workers losing their routine skills are not replaced and manual labor increases. Besides, as ICT capital and abstract labor are complementary, more people train to become high-skill workers and abstract labor rises. Second, the fall in trade costs causes an increase in international trade. In particular, with offshoring, Western European workers supplying routine labor are replaced by Central and Eastern European or Asian workers. As such, it also causes a decrease in routine labor and an increase in manual labor. However, offshoring has no direct consequence on the share of abstract labor. Hence, in the model, only automation has an up-skilling effect, meaning that it drives workers to become high-skill.

Furthermore, I find that the dynamics of the occupational employment distribution are mainly driven by automation. The increase in international trade has no effect on the abstract labor share while it explains only 18% of the decrease in the routine labor share and 43% of the increase in the manual labor share implied by the model. I also show that the impact of trade costs is entirely driven by offshoring. As international trade on final good remains relatively low in proportion of GDP, it barely affects the distribution of employment. Those results presenting automation as the main factor to explain job polarization are consistent with several recent studies focusing on Western European countries (Michaels et al. (2014) or Goos et al. (2014)) but differ with the results of other papers looking at the United States as Cortes et al. (2017) or Eden and Gaggl (2018).

Finally, the cumulative welfare analysis suggests that Western Europe experienced aggregate welfare gains during the period. Computing the Hicksian-equivalent consumption change between 2000 and 2016, the falls in ICT-capital price and trade costs are associated with an increase of almost 2.5% in consumption in Western European countries. International trade causes small but positive welfare gains. Indeed, the fall in trade costs leads to a decrease in the price of tradable goods, allowing individuals to increase consumption. However, 74% of the total welfare gains arise from automation, as it is the sole driver of the increase in the number of high-skill workers. Importantly however, automation has negative welfare effects in the short term. This comes from the fact that consumption and investment must first decrease to pay for the high-skill training of a higher number of individuals. Only after a few periods, per-capita consumption increases as more workers earn the (higher) abstract wage. As the utility is discounted over time, cumulative welfare becomes positive only in 2011 according to my simulations.

The paper is organized as follows. Section 2 reviews the related literature and highlights the contributions of the paper. Section 3 details the model. Section 4 presents the parametrization and the method to compute the exogenous driving forces. Section 5 exhibits the main results and confronts them to the data before running a counterfactual analysis and a welfare exercise. Section 6 concludes.

2 Related literature

The paper relates to two strands of the literature on labor-market polarization: one that looks at the role of automation and one interested in the increase in international trade. Concerning automation, Autor et al. (2003) develop a theory called the Routine-Biased Technical Change (RBTC). Looking at the data from the United States since 1960, they show that, as the cost of computer capital decreased, machines and computers have been replacing workers performing repetitive (routine) tasks. On the contrary, those machines are complementary with complex non-routine (abstract) tasks. As such, routine workers have been forced to train to be able to perform abstract tasks or have had to switch to manual non-routine tasks. As routine tasks are usually at the center of the wage spectrum, they show that this increase in automation has been a major reason for the polarization of employment and wages in the United States.

Following this seminal paper, several authors have conducted econometric analyses to investigate the relation between the increase in investment in machines and job polarization, including for European countries.[3] Among them are Michaels et al. (2014). Looking at ICT-investment data since 1980, they find a similar relation in the U.S. but also Japan and nine Western European countries. An increase in ICT investment has a positive correlation with the number of workers supplying abstract tasks and a negative one with the number of workers supplying routine labor. Goos et al. (2014) focus on labor-market polarization in 16 Western European countries. Looking at data from 1993 to 2010, they find evidence of a decrease in jobs with a strong focus on routine tasks. Those jobs, in the middle of the wage spectrum, have seen their number decrease as they become supplied by machines or, more rarely, offshored. Senftleben-König et al. (2014) and Dauth et al. (2017) find similar consequences of automation on employment polarization in Germany. Finally, using a decrease in taxes on ICT investment in the United Kingdom, Gaggl and Wright (2017) obtain a positive causal relation from ICT investment to employment and earnings of workers performing abstract tasks, and a negative causal relation to employment and earnings of workers performing routine tasks.

In addition to these empirical contributions, theoretical frameworks have been developed to try to formally explain the role of automation in job polarization. Acemoglu and Autor (2011) develop a task-based model to better reproduce this phenomenon than the canonical model. Skills are endogenously allocated to tasks and new technology can replace middle-skill workers. This general framework notably explains the polarization of earnings with a particularly strong increase in the return on abstract skills. Autor and Dorn (2013) build a general equilibrium framework with

[3] See Jaimovich and Siu (2019) for a better view of the literature.

similar characteristics and apply it to U.S. data. They show that automation is the central factor explaining the polarization of employment and earnings. Furthermore, they find that local labor markets that previously specialized in routine occupations saw a stronger decrease in routine labor and a higher rise in service occupations than other areas. Other models were later built by Lee and Shin (2017) or Bárány and Siegel (2018) for example to better explain some other aspects of job polarization.

Another strand of the literature looks at the role of the decrease in the costs of international trade, especially through offshoring, on labor-market polarization.[4] One of the first models was proposed by Feenstra and Hanson (1997). They build a framework with one country with a high-skill specialization (North) and a another with a low-skill specialization (South). They show that an increase in offshoring from the North to the South leads to a decrease in low-skill jobs in the North as they are transferred to the South. But, those new jobs are actually considered high skill in the South in comparison with pre-existing employment. As such, the share of relatively high-skill labor increases in each country. FDI data from the U.S. to Mexico supports their theoretical findings.

Other frameworks were later developed to better fit empirical patterns. Grossman and Rossi-Hansberg (2008) build a two-country model with asymmetric development and with high and low-skill workers. They show that an increase in offshoring to the South leads to the destruction of some low-skill jobs in the North, but that productivity gains arise, bringing an increase in the wage of both low and high-skill workers in the North. Ottaviano et al. (2013) modify the seminal model of Grossman and Rossi-Hansberg (2008) to include several sectors and add low-skill immigration. They find that a reduction in offshoring costs associated with an increase in low-skill immigration lead natives to leave routine tasks for high-skill jobs. Nevertheless, the joint fall in offshoring costs and rise in immigration bring productivity gains, so that the number of native low-skill workers may remain similar or even increase. Eeckhout and Jovanovic (2012) build a sorting model where agents with two different levels of skill can be managers or workers. Productivity mostly depends on the skill level of the firm's manager. They find that economic integration leads to an increase in the share of managers and a decrease in the share of workers in high-income countries, as managers decide to hire workers from low-income countries. Mandelman (2016) develops a stochastic growth model with trade in tasks to investigate the small and medium term effects of a decrease in the cost of communication and transportation between countries. Feeding the model with different driving forces, he concludes that offshoring is the main factor explaining the decrease in middle-skill workers since the 1990s in the United States and the resulting job polarization.

Several papers have also studied the impact of international trade on employment and wage in Western European countries from an empirical point. Based on French data, Biscourp and Kramarz (2007) find evidence of a decrease in production jobs when firms increase their final

[4] See Hummels et al. (2018) for a literature review of the effects of international trade on occupational displacements.

good imports. Mion and Zhu (2013) observe a decrease in employment growth and an increase in skill upgrading for Belgian firms that decide to offshore parts of their production. They explain that the negative effect on employment is larger when offshoring to China. Looking at Germany, Baumgarten et al. (2013) show that, with the increase in offshoring, routine occupations suffer from a negative effect on wage and employment whether or not they are supplied by low-skill workers.

Only a few papers built theoretical frameworks to study the joint impact of offshoring and automation on the distribution of employment. Jung and Mercenier (2014) develop a two-sector general equilibrium model where skills are continuously distributed. Workers are sorted in tasks depending on their skills. As routine tasks get offshored or automated, workers previously supplying them either upgrade to cognitive tasks or downgrade to non-routine non-cognitive tasks. At the same time, through general equilibrium effects, wages increase at both ends of the wage distribution. They find one major difference between the effects of automation and offshoring. Offshoring decreases the number and the wage of workers performing routine tasks homogeneously. On the contrary, automation generates rising inequalities in employment and earnings within routine tasks. Cavenaile (2018) finds similar results by extending the model of Eeckhout and Jovanovic (2012). He includes four occupations and two sectors (service and goods) and adds automation. Only jobs in the goods sector can be offshored or automated. As such, an increase in offshoring or automation forces workers in the goods sector to either become managers if they are relatively high-skill or join the service sector as worker if they are relatively low-skill. This way, job polarization occurs. This paper also reproduces the increase in top income inequality. Finally, Mandelman and Zlate (2021) look at the respective roles of automation, low-skill migration and offshoring between high-income countries in explaining the changes in employment distribution in the United States since 1983. On the one hand, they find that automation and offshoring both decrease middle-skill employment, the latter having the strongest impact. On the other hand, low-skill migration decreases low-skill wages, pushing natives to train and become high-skill.

My paper, by its purpose and modeling strategy, most closely relates to Mandelman and Zlate (2021). While my model tracks Mandelman and Zlate (2021) for the modeling of automation, it is closer to Ottaviano et al. (2013) for the offshoring part. In addition, Mandelman and Zlate (2021) use a theoretical framework and a calibration specifically built for the United States while my focus and parametrization are on Western European countries from 2000 to 2016. To the best of my knowledge, my paper is the first to quantify the respective contributions of automation and offshoring to labor-market polarization in Western European countries using a dynamic general equilibrium framework.

3 Model

3.1 General presentation

The model features three regions representing old members of the European Union or Western European countries (EUR region); new members of the European Union or Central and Eastern European countries (CEE region); and the rest of the world represented by the main countries of South Asia (ROW region). Each region features three types of workers: high-skill workers who acquire the ability to supply abstract tasks through training, middle-skill workers who acquire the ability to supply routine tasks through training, and low-skill workers who supply manual non-routine tasks. Some high and middle-skill workers randomly lose their skills at every period. Manual labor is used to produce non-tradable goods while abstract and routine labor are combined with ICT capital to produce an internationally tradable good. For simplicity, I abstract from non-ICT capital as most of the increase in aggregate capital between 2000 and 2016 is due to ICT capital as its relative price has been falling rapidly over the period. Besides, ICT capital is of great interest when studying job polarization as most empirical studies find it to be complement with abstract labor but substitute with routine labor. For firms of the EUR region, routine tasks can be performed at home or offshored to any other region depending on their marginal cost. For firms of the CEE and ROW regions, all routine tasks are supplied domestically. Given my focus on structural change, I do not consider a government sector and assume financial autarky. In the next paragraphs, I present the details of the model from the perspective of the EUR region. When needed, variables for the CEE and ROW regions are presented respectively with C or R superscripts. Finally, as regions have different relative sizes, all variables are expressed per-capita. The functioning of the model is graphically presented in Appendix C.

3.2 Households

In the EUR region, there is a large family made of a continuum of n individuals.[5] Although members are heterogeneous in terms of skills, family members are insured against income fluctuations: members pool their income to achieve the same level of individual consumption as in Merz (1995). Family members derive utility from consumption C_t. The family head thus maximizes the utility $u(C_t)$:

$$E_t \sum_{s=t}^{\infty} \beta^{s-t} \ln(C_t) \tag{1}$$

subject to the budget constraint:

$$W_{m,t}N_t + \eta_t N_{r,t} + \pi_t N_{a,t} + R_{k,t}K_t + Div_t = P_t(C_t + I_t) + f_{Na,t}N_{Na,t} + f_{Nr,t}N_{Nr,t} \tag{2}$$

Sources of income are presented on the left-hand side while uses of this income are on the right-hand side. On the LHS, for the ease of analysis, I separated income due to the work effort from the premium due to supplying routine or abstract work. Total raw labor income is $W_{m,t}N_t$. This

[5] The CEE family counts n^C individuals and the ROW family $n^R = 1 - n - n^C$ individuals.

corresponds to a unit base wage $W_{m,t}$ multiplied by the number of workers N_t. Low-skill workers $N_{m,t}$ supply manual labor. They only receive the base wage $W_{m,t}$ for their production. Each worker supplying heterogeneous routine tasks $N_{r,t}$ earns a positive premium η_t over the base wage every period.[6] High-skill workers supplying abstract labor $N_{a,t}$ earn the base wage plus a premium π_t that comes from their training and that is higher than the routine premium. The family also earns a return $R_{k,t}$ per unit of ICT capital K_t. Finally, it shares the profit Div_t that is the sum of profits coming from the monopolistic firms producing the tradable good ($Div_{T,t}$) and those producing the non-tradable good ($Div_{N,t}$). On the RHS, the family can consume the final good C_t or invest in the ICT-capital good I_t at a unit price P_t. It also decides to train $N_{Na,t}$ individuals to become high-skill workers by paying the sunk cost $f_{Na,t}$. The latter cost is expressed in terms of raw labor: $f_{Na,t} = f_{Na}W_{m,t}$. Those workers become immediately productive to supply the abstract task. Each period, a share δ_a of high-skill workers sees their set of skills become obsolete and becomes low-skill workers. Similarly, the family decides to train $N_{Nr,t}$ new middle-skill workers who become immediately productive to supply routine tasks. To this end, the family pays the sunk cost $f_{Nr,t} = f_{Nr}W_{m,t}$. As for abstract workers, a share δ_r of middle-skill workers sees their set of skills become obsolete and becomes low-skill workers at each period. As such, the laws of motion for high-skill and middle-skill workers are respectively:

$$N_{a,t} = (1 - \delta_a)N_{a,t-1} + N_{Na,t} \tag{3}$$

$$N_{r,t} = (1 - \delta_r)N_{r,t-1} + N_{Nr,t} \tag{4}$$

As such, low-skill workers $N_{m,t}$ have the following law of motion:

$$N_{m,t} = N_{m,t-1} - N_{Na,t-1} - N_{Nr,t-1} + \delta_a N_{a,t-1} + \delta_r N_{r,t-1} \tag{5}$$

To sum up, the total number of workers N_t is the sum of high-skill workers supplying abstract labor $N_{a,t}$, middle-skill workers supplying routine labor $N_{r,t}$ and low-skill workers $N_{m,t}$

$$N_t = N_{a,t} + N_{r,t} + N_{m,t} \tag{6}$$

I normalize $N_t = 1$, meaning that each amount $N_{o,t}$ with $o = \{a, r, m, Na, Nr\}$ is actually the probability for a worker to be that specific type of worker.

The stock of ICT capital follows a law of motion with an exogenous perturbation $\epsilon_{K,t}$:

$$K_{t+1} = (1 - \delta_K)K_t + \epsilon_{K,t}I_t \tag{7}$$

with δ_K the depreciation rate of capital and $(\epsilon_{K,t})^{-1}$ the relative cost of ICT capital with respect to the price of consumption goods.

[6] Goos et al. (2014) show that workers supplying manual tasks are at bottom of the wage distribution while workers supplying routine tasks are in the middle of the wage distribution.

First-order conditions with respect to C_t, K_{t+1}, I_t, $N_{a,t}$ and $N_{r,t}$ imply:

$$\lambda_t = \beta E_t \left\{ \frac{R_{K,t+1}}{P_{t+1}C_{t+1}} + \lambda_{t+1}(1-\delta_K) \right\} \tag{8}$$

$$\lambda_t = \frac{1}{\epsilon_{K,t}C_t} \tag{9}$$

$$f_{Na,t} = \pi_t + \beta E_t \left\{ (1-\delta_a)\frac{P_tC_t}{P_{t+1}C_{t+1}} f_{Na,t+1} \right\} \tag{10}$$

$$f_{Nr,t} = \eta_t + \beta E_t \left\{ (1-\delta_r)\frac{P_tC_t}{P_{t+1}C_{t+1}} f_{Nr,t+1} \right\} \tag{11}$$

where λ_t is the Lagrange multiplier associated with the law of motion of ICT capital. Equations (8) and (9) give the standard choices for capital and investment. Equations (10) and (11) show that the sunk cost of training must be equal to the expected discounted sum of premiums, taking into account that skills can become obsolete at each period.

Per-capita consumption and investment are defined as Armington aggregators of tradable and non-tradable goods:

$$\nu_t = \left[(\alpha_y)^{\frac{1}{\rho}} (\nu_{H,t})^{\frac{\rho-1}{\rho}} + (1-\alpha_y)^{\frac{1}{\rho}} (\nu_{N,t})^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \tag{12}$$

with $\nu = \{C, I\}$. Variables $\nu_{H,t}$ and $\nu_{N,t}$ respectively stand for the quantities of tradable and non-tradable goods in the bundle and ρ is the elasticity of substitution between tradable and non-tradable goods. Tradable-good quantities $\nu_{H,t}$ are themselves a bundle:

$$\nu_{H,t} = \left[(1-\alpha_C-\alpha_R)^{\frac{1}{\phi}} (\nu_{T,t})^{\frac{\phi-1}{\phi}} + (\alpha_C)^{\frac{1}{\phi}} (\nu^C_{T,t})^{\frac{\phi-1}{\phi}} + (\alpha_R)^{\frac{1}{\phi}} (\nu^R_{T,t})^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}} \tag{13}$$

where α_R and α_C respectively capture openness with the ROW and CEE regions. They both belong to the interval $[0,1]$, and $\alpha_C + \alpha_R < 1$ captures the total degree of trade openness. Variables $\nu_{T,t}$, $\nu^C_{T,t}$ and $\nu^R_{T,t}$ respectively denote the per-capita quantities of EUR, CEE and ROW varieties of tradable goods consumed in the EUR region. Parameter ϕ is the trade elasticity between those tradable goods. Variables $\nu_{N,t}$, $\nu_{T,t}$, $\nu^C_{T,t}$ and $\nu^R_{T,t}$ are themselves bundles of good varieties, respectively defined as:

$$\nu_{N,t} = \left[\left(\frac{1}{n}\right)^{\frac{1}{\gamma_N}} \int_0^n \nu_{N,t}(i)^{\frac{\gamma_N-1}{\gamma_N}} di \right]^{\frac{\gamma_N}{\gamma_N-1}} \tag{14}$$

$$\nu_{T,t} = \left[\left(\frac{1}{n}\right)^{\frac{1}{\gamma_T}} \int_0^n \nu_{T,t}(i)^{\frac{\gamma_T-1}{\gamma_T}} di \right]^{\frac{\gamma_T}{\gamma_T-1}} \tag{15}$$

$$\nu^C_{T,t} = \left[\left(\frac{1}{n^C}\right)^{\frac{1}{\gamma_T}} \int_0^{n^C} \nu^C_{T,t}(i)^{\frac{\gamma_T-1}{\gamma}} di \right]^{\frac{\gamma_T}{\gamma_T-1}} \tag{16}$$

$$\nu^R_{T,t} = \left[\left(\frac{1}{1-n-n^C}\right)^{\frac{1}{\gamma_T}} \int_{n+n^C}^{1} \nu^R_{T,t}(i)^{\frac{\gamma_T-1}{\gamma_T}} di \right]^{\frac{\gamma_T}{\gamma_T-1}} \tag{17}$$

where γ_N and γ_T are the elasticities of substitution respectively for the non-tradable and the tradable varieties of goods. The aggregate price index is given by:

$$P_t = \left[\alpha_y (P_{H,t})^{1-\rho} + (1-\alpha_y)(P_{N,t})^{1-\rho}\right]^{\frac{1}{1-\rho}} \tag{18}$$

where $P_{N,t}$ is the price index of the non-tradable good and $P_{H,t}$ the consumer price index of tradable goods given by:[7]

$$P_{H,t} = \left[(1-\alpha_C-\alpha_R)(P_{T,t})^{1-\phi} + (\alpha_C)(\tau_t^C e_t^C P_{T,t}^C)^{1-\phi} + (\alpha_R)(\tau_t^R e_t^R P_{T,t}^R)^{1-\phi}\right]^{\frac{1}{1-\phi}} \tag{21}$$

where $P_{T,t}$, $P_{T,t}^C$ and $P_{T,t}^R$ denote the producer price indices of the tradable goods respectively from EUR, CEE and ROW regions, e_t^O is the bilateral nominal exchange rate with region $O = \{C, R\}$ and $\tau_t^O = \tau^O \epsilon_{F,t}^O$ is an (exogenous and time-varying) iceberg-melting cost paid to import or export a good with region $O = \{C, R\}$. This iceberg cost takes into account all types of costs to be paid when trading in another region such as trade barriers or transportation and administrative costs.[8]. The price indices are defined as:

$$P_{N,t} = \left[\left(\frac{1}{n}\right)\int_0^n P_{N,t}(i)^{1-\gamma_N} di\right]^{\frac{1}{1-\gamma_N}} \tag{22}$$

$$P_{T,t} = \left[\left(\frac{1}{n}\right)\int_0^n P_{T,t}(i)^{1-\gamma_T} di\right]^{\frac{1}{1-\gamma_T}} \tag{23}$$

$$P_{T,t}^C = \left[\left(\frac{1}{n^C}\right)\int_0^{n^C} P_{T,t}^C(i)^{1-\gamma_T} di\right]^{\frac{1}{1-\gamma_T}} \tag{24}$$

$$P_{T,t}^R = \left[\left(\frac{1}{1-n-n^C}\right)\int_{n+n^C}^1 P_{T,t}^R(i)^{1-\gamma_T} di\right]^{\frac{1}{1-\gamma_T}} \tag{25}$$

Optimization gives the following demand functions in the EUR region for variety i of the non-tradable good, the EUR-produced, CEE-produced and ROW-produced tradable goods respectively :

[7] The consumer price indices of tradable goods in the CEE region and the ROW region are respectively:

$$P_{H,t}^C = \left[(1-\alpha_E^C-\alpha_R^C)(P_{T,t}^C)^{1-\phi} + (\alpha_E^C)(\tau_t^C 1/e_t^C P_{T,t})^{1-\phi} + (\alpha_R^C)(\tau_t^{CR} e_t^R/e_t^C P_{T,t}^R)^{1-\phi}\right]^{\frac{1}{1-\phi}} \tag{19}$$

$$P_{H,t}^R = \left[(1-\alpha_C^R-\alpha_E^R)(P_{T,t}^R)^{1-\phi} + (\alpha_C^R)(\tau_t^{CR} e_t^C/e_t^R P_{T,t}^C)^{1-\phi} + (\alpha_E^R)(\tau_t^R 1/e_t^R P_{T,t})^{1-\phi}\right]^{\frac{1}{1-\phi}} \tag{20}$$

[8] As usual, the iceberg trade costs are considered symmetric: the iceberg cost to export from EUR to CEE is the same as the cost to export from CEE to EUR

$$\nu_{N,t}(i) = \left(\frac{1-\alpha_y}{n}\right)\left(\frac{P_{N,t}(i)}{P_{N,t}}\right)^{-\gamma_N}\left(\frac{P_{N,t}}{P_t}\right)^{-\rho}(n\nu_t) \tag{26}$$

$$\nu_{T,t}(i) = \left(\frac{\alpha_y(1-\alpha_C-\alpha_R)}{n}\right)\left(\frac{P_{T,t}(i)}{P_{T,t}}\right)^{-\gamma_T}\left(\frac{P_{T,t}}{P_{H,t}}\right)^{-\phi}\left(\frac{P_{H,t}}{P_t}\right)^{-\rho}(n\nu_t) \tag{27}$$

$$\nu^C_{T,t}(i) = \left(\frac{\alpha_y\alpha_C}{n^C}\right)\left(\frac{P^C_{T,t}(i)}{P^C_{T,t}}\right)^{-\gamma_T}\left(\frac{\tau^C_t e^C_t P^C_{T,t}}{P_{H,t}}\right)^{-\phi}\left(\frac{P_{H,t}}{P_t}\right)^{-\rho}(n\nu_t) \tag{28}$$

$$\nu^R_{T,t}(i) = \left(\frac{\alpha_y\alpha_R}{1-n-n^C}\right)\left(\frac{P^R_{T,t}(i)}{P^R_{T,t}}\right)^{-\gamma_T}\left(\frac{\tau^R_t e^R_t P^R_{T,t}}{P_{H,t}}\right)^{-\phi}\left(\frac{P_{H,t}}{P_t}\right)^{-\rho}(n\nu_t) \tag{29}$$

3.3 Production

3.3.1 Tradable-good production

There is a continuum of monopolistic firms producing different varieties i of the tradable good. As in Mandelman and Zlate (2021), the tradable good is produced combining abstract tasks, routine tasks and ICT capital according to the following production function:

$$Y_{T,t}(i) = \left\{\alpha_r^{\frac{1}{\theta}} R_t(i)^{\frac{\theta-1}{\theta}} + (1-\alpha_r)^{\frac{1}{\theta}}\left[\alpha_k^{\frac{1}{\sigma}} K_t(i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha_k)^{\frac{1}{\sigma}} A_t(i)^{\frac{\sigma-1}{\sigma}}\right]^{\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{\theta-1}{\theta}\right)}\right\}^{\frac{\theta}{\theta-1}} \tag{30}$$

with $\theta > \sigma > 0$. $A_t(i)$ is the amount of abstract input supplied by high-skill workers and $R_t(i)$ is the routine input provided by domestic middle-skill workers or by foreign middle-skill workers through offshoring in firm i. The elasticity of substitution between capital and routine labor θ is assumed to be larger than the elasticity of substitution between capital and abstract labor σ. Hence, ICT capital is a relative complement to abstract labor and a relative substitute to routine labor. Each period, firms maximize the profits they rebate to the large family:

$$Div_{T,t}(i) = \frac{P_{T,t}(i)}{P_{T,t}} Y_{T,t}(i) - r_{k,t}(i)K_t(i) - mc_{a,t}(i)A_t(i) - mc_{r,t}(i)R_t(i) \tag{31}$$

where $Div_{T,t}(i)$ is the profit of firm i producing the tradable good, $mc_{a,t}(i)$ and $mc_{r,t}(i)$ are the real marginal costs of abstract and routine tasks for firm i to be defined below and $r_{k,t}(i) = R_{k,t}(i)/P_{T,t}$ is the real rate of return of capital for firm i. Optimization gives the following factor demands:

$$R_t(i) = \alpha_r\left(\frac{mc_{r,t}(i)}{mc_{T,t}(i)}\right)^{-\theta} Y_{T,t}(i) \tag{32}$$

$$A_t(i) = (1-\alpha_r)(1-\alpha_k)\left(\frac{mc_{a,t}(i)}{mc_{ka,t}(i)}\right)^{-\sigma}\left(\frac{mc_{ka,t}(i)}{mc_{T,t}(i)}\right)^{-\theta} Y_{T,t}(i) \tag{33}$$

$$K_t(i) = (1-\alpha_r)\alpha_k\left(\frac{r_{k,t}(i)}{mc_{ka,t}(i)}\right)^{-\sigma}\left(\frac{mc_{ka,t}(i)}{mc_{T,t}(i)}\right)^{-\theta} Y_{T,t}(i) \tag{34}$$

where $mc_{ka,t}(i) = \left[\alpha_k (r_{K,t}(i))^{1-\sigma} + (1-\alpha_k)(mc_{a,t}(i))^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ and $mc_{T,t}(i)$ is the real marginal cost of the tradable good in firm i. As firms have the same optimizing behavior, aggregation is easily done and they choose the same price: $P_{T,t}(i) = P_{T,t}$. For simplicity and without loss of generality, I choose $P_{T,t} = 1$. As such, optimization gives us $mc_{T,t}(i) = mc_{T,t} = \frac{\gamma_T - 1}{\gamma_T}$, a usual condition.

3.3.2 Abstract tasks

High-skill workers are perfect substitutes between each others and provide abstract tasks used in the production of the tradable good with the same productivity. Abstract labor is the only input required for the production of abstract tasks, defined as:

$$A_t(i) = N_{a,t}(i)\Lambda x_{a,t} \tag{35}$$

where $N_{a,t}(i)$ is the number of high-skill workers in firm i and the expression $\Lambda x_{a,t}$ indicates the productivity of workers. Parameter Λ expresses the productivity differential between the different regions that results from technological differences. It is normalized to one for the EUR region and is less than one for the other regions (more details are provided in the Section dedicated to the parametrization). The variable $x_{a,t} > 1$ tracks the relative productivity of abstract workers. The converse variable for manual labor x_m is normalized to one. Therefore, it can be seen as the productivity differential between abstract and manual labor. Abstract workers are paid a real wage $w_{a,t} = W_{a,t}/P_{T,t}$. High-skill workers are perfect substitutes, meaning that aggregation is straightforward. Therefore, the marginal cost of the abstract production is equal to the abstract wage divided by the productivity differential parameters for all firms: $mc_{a,t}(i) = mc_{a,t} = \frac{w_{a,t}}{\Lambda x_{a,t}}$. Finally, the premium π_t is the difference between the income earned by abstract workers and their income if they had instead supplied manual tasks:

$$\frac{\pi_t}{P_{T,t}} = w_{a,t} - w_{m,t} \tag{36}$$

3.3.3 Routine tasks

General presentation. Routine input is composed of non-substitutable routine tasks indexed by j.[9] Those tasks follow a uniform distribution on the interval $[0, j_{max}]$ with c.d.f. $G(\cdot)$. Each routine task j can be supplied by any middle-skill worker with the same productivity, domestically (D), or through offshoring to the CEE region (C) or the ROW region (R). As such, index j has no influence for domestic workers, but it is crucial for the offshoring process as it indicates the complexity to offshore a specific task. As the three types of workers are perfectly substitutable for any routine task, firms choose the factor of production with the lowest marginal cost.

A domestic worker supplies an effort $l_t = r_t \Lambda x_{r,t}$ where $x_{r,t}$ tracks the difference of productivity between routine and manual labor and r_t, normalized to 1, is the effort needed to produce any

[9]For this part of the model, I mostly use the modeling strategy developed in Ottaviano et al. (2013). I make some changes to their model as replacing migrant workers by a second level of offshoring.

individual task. Therefore, the effort required to produce a task is different from the effort supplied by a worker. Input requirements are considered identical for each firm, meaning that the index i is not necessary to express task effort. I consider that when offshoring firms open a subsidiary in the foreign region and give foreign workers access to the same technology as domestic workers. This means that foreign workers supplying routine labor for EUR firms have the same productivity as domestic EUR routine workers. As such, when working for a EUR firm, each CEE or ROW worker supplies the same effort l_t. Thus, the routine input in firm i is produced according to the following production function:

$$R_t(i) = N_{f,t}(i) x_{r,t} \Lambda r_t \tag{37}$$

with $N_{f,t}(i)$ the number of routine workers in firm i. As explained before, the index j has no influence on the productivity of workers and therefore does not appear in the production function. However, the index is necessary for the expression of the companion price index as the cost of a task depends on the location of the worker:

$$mc_{r,t}(i) = \int_0^{j_{max}} c_{r,t}(i,j) dj \tag{38}$$

with $c_{r,t}(i,j)$ the cost of task j in firm i. Each firm pays domestic workers the identical real wage $w_{r,t} = W_{r,t}/P_{T,t}$ that takes into account the premium due to training. We can simply obtain the premium income earned by each domestic routine worker expressed in real terms as the difference of income between what they earn and what they would have earned if employed to supply manual tasks:

$$\frac{\eta_t}{P_{T,t}} = w_{r,t} - w_{m,t} \tag{39}$$

Offshoring options. Mandelman and Zlate (2021) consider that for U.S. firms offshoring mostly happens with firms of countries that have the same level of development and is due to countries' specializations. However, it is not the best way to represent offshoring in the present case. As explained in Eurofound (2016), a large amount of offshoring between countries with a similar level of development takes place for Western European countries. But, it almost only occurs between countries of the region (for instance, from France to Italy or Spain). This type of offshoring should have little or no effect for the aggregate distribution of employment in the EUR region. Therefore, offshoring due to specialization is not a main concern here and is not taken into account. In this model, I look at offshoring that EUR firms implement for cost reasons, towards countries with a lower level of development.[10] This type of offshoring should indeed have an effect on employment

[10] In the model, the impossibility for CEE firms to offshore to the EUR region or for ROW firms to offshore to any region is simply due to the fact that $w_{r,t}/T_t^R > w_{r,t}^C T_t^C / T_t^R > w_{r,t}^R$ as explained below. Therefore, it is always cheaper for ROW firms to produce domestically than to offshore. Similarly, there is no task that is cheaper to offshore to the EUR region than to produce domestically for CEE firms. Offshoring by CEE firms to the ROW region could be added to the model. However, it has very little impact on the dynamics in the EUR region. As such, this type of offshoring is not included to simplify the model. Nevertheless, the model and results with offshoring CEE firms are presented in Appendix F.

distribution in Western European countries.

When offshoring, firms do not pay workers according to their productivity. They pay them the amount they would have earned if employed by their national firms to supply routine tasks. Indeed, all routine workers of a same region are identical and the difference in productivity is simply due to the difference in firms' technology. Therefore, EUR firms pay CEE workers $w_{r,t}^C T_t^C$, with $w_{r,t}^C T_t^C$ the routine CEE wage expressed in the currency of the EUR region. The variable $T_t^C = e_t^C P_{T,t}^C / P_{T,t}$ is the terms of trade between the EUR region and the CEE region. Similarly, a ROW worker is paid a wage $w_{r,t}^R T_t^R$ when employed by EUR firms, with $T_t^R = e_t^R P_{T,t}^R / P_{T,t}$ the terms of trade between EUR and ROW. Those wages are also identical whatever the offshoring firm.

Firms have to pay a supplementary cost $F_t^O(j) = \zeta^O(j)\tau_t^O$ for $O = \{C, R\}$ and with τ_t^O the trade cost defined earlier for each task produced abroad. The variable $\zeta^O(j) = z^O(1+j)$ is a task-specific cost that increases with the index j: the higher j, the more complex it is to offshore the task, and thus the higher the offshoring cost. A high j indicates for example the importance of knowing the firm home language or its culture to perform the task. It may also illustrates that the skills required to perform the task are absent in the region and workers must be trained to perform it.

Location decisions. Given the above assumptions, the costs to produce a specific task domestically $c_{D,t}(j) = c_{D,t}$, to offshore it to the CEE region $c_{OC,t}(j)$ or to the ROW region $c_{OR,t}(j)$ are expressed as follows:

$$c_{D,t} = \frac{w_{r,t}}{x_{r,t}\Lambda} \tag{40}$$

$$c_{OC,t}(j) = F_t^C(j)\frac{w_{r,t}^C T_t^C}{x_{r,t}\Lambda} \tag{41}$$

$$c_{OR,t}(j) = F_t^R(j)\frac{w_{r,t}^R T_t^R}{x_{r,t}\Lambda} \tag{42}$$

The assumption of perfect substitution means that a task is offshored to the CEE region rather than produced domestically whenever:

$$c_{D,t} \geq c_{OC,t}(j) \tag{43}$$

To insure that some offshoring to the CEE region takes place, we need to assume that $c_{D,t} > c_{OC,t}(0)$. Similarly, a task is offshored to the ROW region rather than produced domestically whenever:

$$c_{D,t} \geq c_{OR,t}(j) \tag{44}$$

and I assume that $c_{D,t} > c_{OR,t}(0)$. Finally, a task is offshored to region ROW rather than to region CEE whenever:

$$c_{OC,t}(j) \geq c_{OR,t}(j) \tag{45}$$

To allocate tasks between both types of offshoring, I need two other assumptions. First, I consider that $c_{OC,t}(0) \geq c_{OR,t}(0)$.[11] Second, I assume that $(\zeta_t^C(j))' < (\zeta_t^R(j))'$ so that the difficulty to offshore to region ROW increases faster in j than the difficulty to offshore to region CEE.[12] With those assumptions, offshoring occurs in each region. The previous assumptions imply that there is only one time-dependent "marginal ROW offshored task" $j = J_{CR,t}$ such that

$$c_{OC,t}(J_{CR,t}) = c_{OR,t}(J_{CR,t}) \tag{46}$$

This means that for all tasks $j \leq J_{CR,t}$, it is cheaper to offshore tasks to the ROW region than to the CEE region. On the contrary, it is cheaper to offshore tasks to the CEE region than to the ROW region when $j \geq J_{CR,t}$. Moreover, for all three types of workers to supply labor, we need $c_{OC,t}(J_{CR,t}) < c_{D,t} < c_{OC,t}(j_{max})$. This gives us a "marginal CEE offshored task" $j = J_{DC,t}$ such that

$$c_{D,t} = c_{OC,t}(J_{DC,t}) \tag{47}$$

The resulting task allocation is presented in Figure 2 and the cost of each task is defined as follows whatever the EUR firm:

$$c_t(j) = c_t(i,j) = \begin{cases} c_{OR,t}(j) & = F_t^R(j)\frac{w_{r,t}^R T_t^R}{x_{r,t}\Lambda} & 0 \leq j < J_{CR,t} \\ c_{OC,t}(j) & = F_t^C(j)\frac{w_{r,t}^C T_t^C}{x_{r,t}\Lambda} & J_{CR,t} \leq j < J_{DC,t} \\ c_{D,t} & = \frac{w_{r,t}}{x_{r,t}\Lambda} & J_{DC,t} \leq j < j_{max} \end{cases}$$

The routine average marginal cost $mc_{r,t}(i) = mc_{r,t}$ can be expressed as the weighted average of the average cost of a task produced by each type of workers:

$$mc_{r,t}(i) = mc_{r,t} = G(J_{CR,t})mc_{OR,t} + \left[G(J_{DC,t}) - G(J_{CR,t})\right]mc_{OC,t} + \left[1 - G(J_{DC,t})\right]mc_{D,t} \tag{48}$$

with the average (marginal) cost of a task produced by a domestic worker, a worker of the CEE region, and of the ROW region expressed respectively as:

$$mc_{D,t} = \frac{w_{r,t}}{x_{r,t}\Lambda} \tag{49}$$

$$mc_{OC,t} = \frac{1}{J_{DC,t} - J_{CR,t}} \int_{J_{CR,t}}^{J_{DC,t}} F_t^C(j)\frac{w_{r,t}^C T_t^C}{x_{r,t}\Lambda}\, dj \tag{50}$$

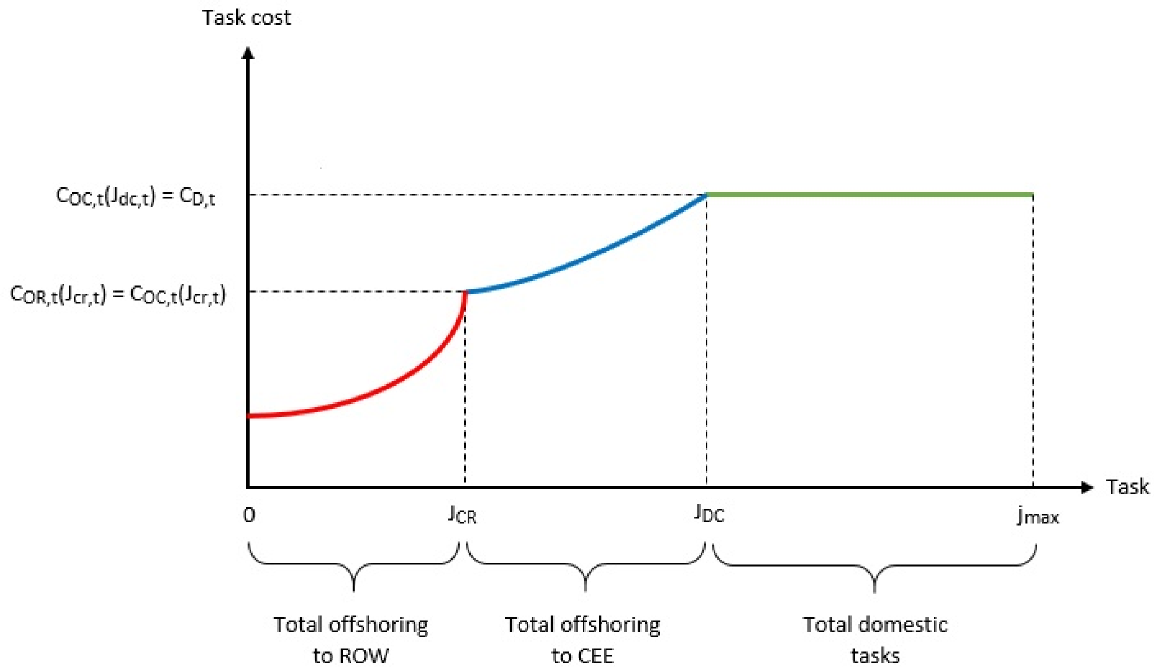
$$mc_{OR,t} = \frac{1}{J_{CR,t}} \int_0^{J_{CR,t}} F_t^R(j)\frac{w_{r,t}^R T_t^R}{x_{r,t}\Lambda}\, dj \tag{51}$$

As firms have the same optimizing behavior and workers have the same productivity, aggregation

[11] This assumption is easily justified by the fact that wages are lower in countries of Southern Asia than in Central and Eastern Europe.

[12] This can easily be justified by the stronger difference in culture and language between Western Europe and Asia than between both regions of Europe.

Figure 2: Routine worker decision



is easy. The total number of workers supplying routine tasks for the EUR firms is $N_{f,t} = N_{D,t} + N_{OC,t} + N_{OR,t}$ where $N_{OR,t}$, $N_{OC,t}$ and $N_{D,t}$ are respectively the amount of ROW workers, CEE workers and domestic workers supplying routine labor for EUR firms. As EUR routine workers can only work for domestic firms, $N_{D,t} = N_{r,t}$. We can express the shares of each type of workers over the number of workers producing routine tasks for EUR firms as:

$$\frac{N_{OR,t}}{N_{f,t}} = G(J_{CR,t}), \qquad \frac{N_{OC,t}}{N_{f,t}} = G(J_{DC,t}) - G(J_{CR,t}), \qquad \frac{N_{D,t}}{N_{f,t}} = 1 - G(J_{DC,t}) \tag{52}$$

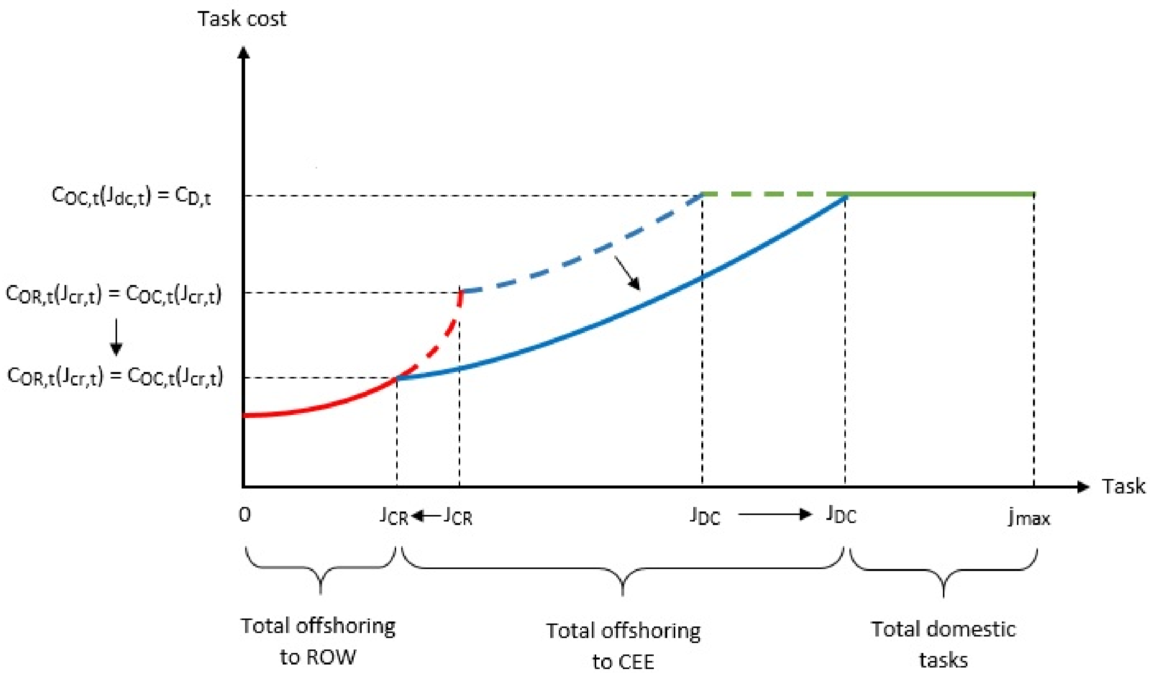
Finally, given the assumption of uniform distribution, we can easily define the location decision cutoffs as:

$$J_{CR,t} = j_{max}\frac{N_{OR,t}}{N_{f,t}}, \qquad J_{DC,t} = j_{max}\frac{N_{OC,t} + N_{OR,t}}{N_{f,t}} \tag{53}$$

Figure 3 indicates the direct effect of a decrease in the trade cost between the EUR and CEE regions τ_t^C on the shares of each type of workers. For any task, the cost of offshoring to the CEE region becomes lower. As such, it has the direct effect of increasing the share of the tasks offshored to the CEE region at the expense of both domestic workers and ROW offshoring. Besides, the cost at which offshoring to the ROW region and the CEE region is equal decreases. Then, Figure 4 shows the direct effect of a decrease in the trade cost between the EUR and ROW regions τ^R on the offshoring decision. This time, the cost of offshoring any task to the ROW region becomes lower. As a consequence, the share of routine tasks offshored to the ROW region logically increases. But, the direct impact only diminishes the share of tasks offshored to the

CEE region. It has no effect on domestic workers (except if the trade cost decreases so much that there is no offshoring to the CEE region anymore). This time, the cost at which offshoring to the CEE or ROW regions is identical increases. If both trade costs decrease at the same time, it has for direct consequence a decrease in the amount of tasks produced domestically as more work is offshored. However, the direct effect on each type of offshoring is unknown and depends on the relative size of the decrease in each trade cost.

Figure 3: Direct effect of a decrease in the trade cost between the EUR and CEE regions



Routine tasks in the other regions. In the CEE region, firms only hire domestic workers to supply routine tasks.[13] Each worker supplies

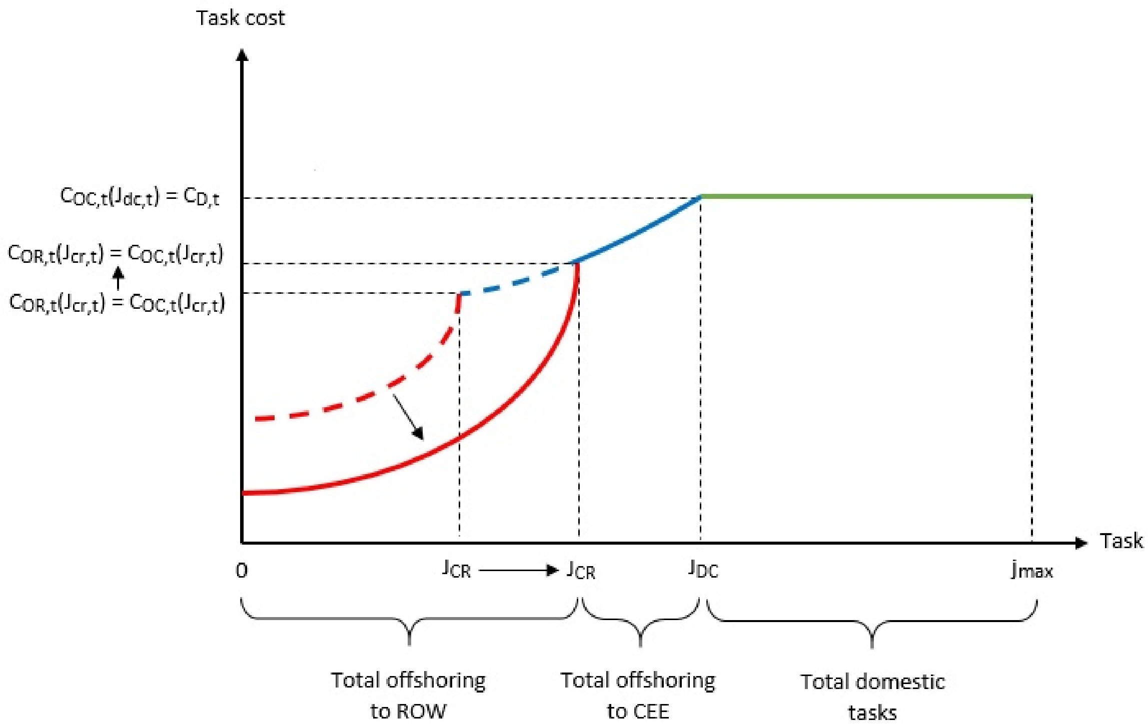
$$l_t^C = r_t^C \Lambda^C x_r \tag{54}$$

They are paid the same real wage $w_{r,t}^C = W_{r,t}^C / P_{T,t}^C$. The marginal cost is equal to the wage divided by the productivity differential parameters: $mc_{r,t}^C(i) = mc_{r,t}^C = \frac{w_{r,t}^C}{\Lambda_t^C x_r}$ for any task. The total number of workers providing routine labor for CEE firms is $N_{f,t}^C = N_{D,t}^C$. We can also express the number of workers supplying routine tasks as the sum of routine workers working domestically and those working for EUR firms:

$$N_{r,t}^C = \left(N_{D,t}^C + \frac{n}{n^C} N_{OC,t} \right) \tag{55}$$

[13]The same equations stand for the ROW region

Figure 4: Direct effect of a decrease in the trade cost between the EUR and ROW regions



3.4 Non-tradable sector

Production in the non-tradable sector is operated by monopolistic firms that only use manual labor as input. Low-skill workers supply manual tasks with the same productivity. As such, the non-tradable production function $Y_{N,t}(i)$ for firm i is defined as

$$Y_{N,t}(i) = N_{m,t}(i)\Lambda x_{m,t} \tag{56}$$

with $x_{m,t}$ normalized to 1 as explained before. Those firms want to maximize the profits they rebate to the domestic family:

$$Div_{N,t}(i) = \frac{P_{N,t}(i)}{P_{N,t}}Y_{N,t}(i) - mc_{m,t}(i)Y_{N,t}(i) \tag{57}$$

with $Div_{N,t}(i)$ the profits of a firm i that produces the non-tradable good and $mc_{m,t}(i)$ the real marginal cost to produce the non-tradable good in firm i. In each firm, workers earn the basic real wage $w_{m,t} = W_{m,t}/P_{T,t}$. As such, the marginal cost equals the wage divided by the productivity differential: $mc_{m,t}(i) = \frac{w_{m,t}}{\Lambda x_{m,t}}$. Furthermore, due to their maximizing behaviors, firms choose the same price. This means that $P_{N,t} = P_{N,t}(i)$ and that $mc_{m,t} = mc_{m,t}(i) = \frac{\gamma_N - 1}{\gamma_N} P_{N_t}$.

3.5 Equilibrium

Aggregate production is simply the sum of productions of tradable and non-tradable goods:

$$Y_t = Y_{T,t} + Y_{N,t} \tag{58}$$

where the aggregate productions of the tradable good $Y_{T,t}$ and of the non-tradable good $Y_{N,t}$ are respectively:

$$Y_{T,t} = \left[\left(\frac{1}{n}\right)^{\frac{1}{\gamma_T}} \int_0^n Y_{T,t}(i)^{\frac{\gamma_T-1}{\gamma_T}} di\right]^{\frac{\gamma_T}{\gamma_T-1}} \tag{59}$$

$$Y_{N,t} = \left[\left(\frac{1}{n}\right)^{\frac{1}{\gamma_N}} \int_0^n Y_{N,t}(i)^{\frac{\gamma_N-1}{\gamma_N}} di\right]^{\frac{\gamma_N}{\gamma_N-1}} \tag{60}$$

The demand for non-tradable goods is divided between consumption and investment. As such, we obtain respectively for EUR, CEE and ROW regions the following equations for the demand of non-tradable goods:

$$Y_{N,t} = \left(\frac{P_{N,t}}{P_t}\right)^{-\rho}(1-\alpha_y)(C_t + I_t) \tag{61}$$

$$Y^C_{N,t} = \left(\frac{P^C_{N,t}}{P^C_t}\right)^{-\rho}(1-\alpha^C_y)(C^C_t + I^C_t) \tag{62}$$

$$Y^R_{N,t} = \left(\frac{P^R_{N,t}}{P^R_t}\right)^{-\rho}(1-\alpha^R_y)(C^R_t + I^R_t) \tag{63}$$

Tradable goods can be used for consumption and investment but also for the training costs. Therefore, demands for EUR, CEE and ROW tradable goods are expressed respectively as:

$$Y_{T,t} = \frac{f_{Na,t}}{P_t}N_{Na,t} + \frac{f_{Nr,t}}{P_t}N_{Nr,t} + frac\Upsilon_t P_t + y^E_{E,t} + y^C_{E,t} + y^R_{E,t} \tag{64}$$

$$Y^C_{T,t} = \frac{f^C_{Na,t}}{P^C_t}N^C_{Na,t} + \frac{f^C_{Nr,t}}{P^C_t}N^C_{Nr,t} + y^C_{C,t} + y^E_{C,t} + y^R_{C,t} \tag{65}$$

$$Y^R_{T,t} = \frac{f^R_{Na,t}}{P^R_t}N^R_{Na,t} + \frac{f^R_{Nr,t}}{P^R_t}N^R_{Nr,t} + y^R_{R,t} + y^E_{R,t} + y^C_{R,t} \tag{66}$$

with $\Upsilon_t = \int_{J_{CR,t}}^{J_{DC,t}} (F^C_t(j)-1) w^C_{r,t} T^C_t N_{OC,t}\, dj + \int_1^{J_{CR,t}} (F^R_t(j)-1) w^R_{r,t} T^R_t N_{OR,t} dj$ the supplementary offshoring cost and $y^J_{I,t}$ total consumption and investment demand in region J for the tradable good from region I.[14] As there is no financial markets, the value of the tasks offshored abroad plus the imports of tradable goods must equal the value of the received offshored tasks plus the exports of tradable goods. Hence, we obtain the following equations of international trade for

[14]Their precise expressions are given in Appendix B.

respectively the EUR, CEE and ROW regions:[15]

$$n\Big[N_{OR,t}w^R_{r,t}T^R_t + N_{OC,t}w^C_{r,t}T^C_t\Big]\frac{P_{T,t}}{P_t} \\ +n^C y^E_{C,t}S^C_t + n^R y^E_{R,t}S^R_t = n\big(y^C_{E,t} + y^R_{E,t}\big) + \Gamma \tag{67}$$

$$n^R y^C_{R,t}S^{CR}_t + n\frac{y^C_{E,t}}{S^C_t} = N_{OC,t}w^C_{r,t}n\frac{P^C_{T,t}}{P^C_t} + n^C\big(y^E_{C,t} + y^R_{C,t}\big) + \Gamma^C \tag{68}$$

$$n\frac{y^R_{E,t}}{S^R_t} + n^C\frac{y^R_{C,t}}{S^{CR}_t} = N_{OR,t}w^R_{r,t}n\frac{P^R_{T,t}}{P^R_t} + n^R\big(y^E_{R,t} + y^C_{R,t}\big) + \Gamma^R \tag{69}$$

where S_t is the real exchange rate in terms of the aggregate price index P_t: $S^C_t = P^C_t/P_t$. Besides, Γ, Γ^C and Γ^R are respectively the steady-state trade deficits of the EUR, CEE and ROW regions with $\Gamma^R = -\frac{\Gamma}{S^R} - \frac{\Gamma^C}{S^{CR}}$.

4 Parameter values and driving forces

4.1 Parameter values

Size and preferences Most parameters are calibrated to match targets for the year 2000, the starting point of the analysis. The three regions of the model represent the different areas of interest of the paper. The EUR region is composed of the fifteen countries that joined the European Union before 2004.[16] The CEE region is constituted of the countries of Central and Eastern Europe that joined the European Union since 2004.[17] Finally, the ROW region includes the developing countries of Asia that are the main partners of the European Union: China, India and Indonesia. Therefore, the size of each region represents its non-agricultural labor force: The EUR, CEE and ROW countries have a respective size of $n = 0.23$, $n^C = 0.05$, $n^R = 0.72$. Besides, as I am focusing on structural changes and not business cycle issues, a period corresponds to a year. Hence, β is calibrated to 0.96.

Employment and labor productivity. The relative amount of each type of labor is set to match labor-force weighted average for each region using the data from the International Labour Organization database (ILOSTAT) and the CEDEFOP for 2000.[18] This gives the following shares for the EUR region: $\bar{N}_a = 38.5\%$, $\bar{N}_r = 34.4\%$ and $\bar{N}_m = 27.1\%$. For the CEE region, we have $\bar{N}^C_a = 36.1\%$, $\bar{N}^C_r = 38.0\%$ and $\bar{N}^C_m = 25.9\%$; and for the ROW region, I obtain $\bar{N}^R_a = 23.5\%$, $\bar{N}^R_r = 44.6\%$ and $\bar{N}^R_m = 31.9\%$. Concerning the earnings, data is not available for all countries. Nevertheless, we can obtain some regional estimates by using data from the ILOSTAT. Earnings

[15] As tariffs are only a small share of the trade costs, I consider that all supplementary trade and offshoring costs are purely wasteful frictions, they are not rebated to households.

[16] Those countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom.

[17] Those countries are Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia.

[18] The precise division between the three categories is presented in Appendix A.

of routine workers are around 2.4 times higher in the EUR region than the CEE region and 8 times higher in the EUR region than in the ROW region. I use those data to set the productivity differential between countries: $\Lambda = 1$, $\Lambda^C = 1/2.4$ and $\Lambda^R = 1/8$. I use the same data to set the productivity differentials between sectors: $x_r = 1.3$ and $x_a = 2.2$. Furthermore, the annual job separation rate is $\delta_a = \delta_r = 0.115$, which corresponds to a 3% quarterly separation rate as found for European countries in Maillard (2020) based on the country estimates in Hobijn and Şahin (2009). These numbers imply an abstract training cost of $f_{Na} = 7.54$ and a routine training cost of $f_{Nr} = 1.89$.

Production. The depreciation rate of capital is $\delta_k = 0.20$ as estimated by Eden and Gaggl (2018). Besides, α_k is calibrated to match the following shares of ICT-capital income in total income: 6.5% for EUR, 5% for CEE and 1% for ROW.[19] As such, $\alpha_k = 0.195$, $\alpha_k^C = 0.149$ and $\alpha_k^R = 0.048$. Moreover, as a consequence of matching the shares of routine labor, abstract labor and ICT capital with the data, I must impose $\alpha_r = 0.528$, $\alpha_r^C = 0.485$ and $\alpha_r^R = 0.568$. The elasticity of substitution between tradable varieties γ_T and between non-tradable varieties γ_N are both set to 6 as in Brückner and Pappa (2012), which produces a gross steady-state markup of 20%. I follow Mandelman and Zlate (2021) for the elasticity of substitution between tradable and non-tradable goods ($\rho = 0.44$) and for the elasticity of substitution between ICT capital and abstract labor ($\sigma = 0.67$). Finally, I impose $\theta = 5$ for the elasticity between abstract and routine labor, a value that provides the best fit of the model with the data in terms of offshoring and polarization.[20]

Offshoring, trade and openness. The share of routine labor that is offshored is pinned down using the World Input-Output Tables (WIOT). Those tables report imports and demand of domestic goods by firms and final consumers by sector and country of origin with a high level of disaggregation (see Timmer et al. (2015) for more details). I consider that offshorable tasks correspond to production made by the manufacturing sector for the manufacturing sector. By summing this type of imports from each country in each region, I obtain the share of those goods received by the EUR region from CEE and ROW regions. I consider that this share corresponds to the share of routine labor offshored by firms of the EUR region. As such, I find that the share of routine labor offshored to ROW is $G(J_{OR}) = 0.9\%$ and that the share routine labor offshored to CEE is $G(J_{DC}) - G(J_{OR}) = 1.9\%$. I choose $j_{max} = 1.5$ to match as closely as possible offshoring data over the period 2000-2016. Given the target quantity of offshoring, the level of trade costs and the wage differentials between countries, the cost parameters for offshoring to the CEE and ROW regions are respectively $z^C = 1.492$ and $z^R = 4.218$. As usual in the international macroeconomic literature, I choose a value of $\phi = 1.5$ for the trade elasticity. I also normalize the terms of trade $\bar{T}^C = \bar{T}^R = \bar{T}^{CR} = 1$ in the steady-state.[21] The size of the openness towards each region are set to match the ratio of import to final-good demand in each region,

[19] The calibration for the EUR region follows the estimation of Eden and Gaggl (2018) for the United States when removing non-ICT capital.

[20] Results for a lower θ are presented in Appendix E.2 and commented in details at the end of Section 5.2.

[21] As an alternative, I could set terms of trade at the value that yields a zero steady-state trade deficit. The results are basically insensitive.

using the WIOT.[22] I obtain $\alpha_C = 0.0121$, $\alpha_R = 0.0168$, $\alpha_E^C = 0.2314$, $\alpha_R^C = 0.0161$, $\alpha_E^R = 0.0511$, $\alpha_C^R = 0.0023$. Those numbers imply the following small trade surplus for the EUR and ROW regions: $\Gamma = -0.0004$ and $\Gamma^R = -0.0003$ and a trade deficit of $\Gamma^C = 0.0007$ for the CEE region. Finally, consistency between the chosen parameter values and the structural equations of the model constrains the size of the tradable-good sector and requires $\alpha_y = 0.834$, $\alpha_y^C = 0.956$ and $\alpha_y^R = 0.747$. Parameter values are summarized in Table 1.

Table 1: Parameter values for the baseline model

Common parameters	**Symbol**	**Value**		
Discount factor	β	0.96		
Depreciation rate of ICT capital	δ_K	0.20		
Job separation rates	$\delta_a = \delta_r$	0.115		
Cost of abstract training	f_{Na}	7.54		
Cost of routine training	f_{Nr}	1.89		
Elasticity of substitution tradable varieties	γ_T	6		
Elasticity of substitution non-tradable varieties	γ_N	6		
Trade elasticity	ϕ	1.5		
Elasticity of substitution tradable and non-tradable goods	ρ	0.44		
Elasticity of substitution ICT capital and abstract labor	σ	0.67		
Elasticity of substitution routine and abstract labor	θ	5		
Steady-state routine productivity	$\bar{x}_r$	1.3		
Steady-state abstract productivity	$\bar{x}_a$	2.2		
Trade and offshoring parameters	**Symbol**	**Value**		
Share of routine production offshored to CEE	$\bar{G}(J_{DC}) - \bar{G}(J_{CR})$	0.019		
Share of routine production offshored to ROW	$\bar{G}(J_{CR})$	0.009		
Trade cost between EUR and CEE	τ^C	1.6		
Trade cost between EUR and ROW	τ^R	2.02		
Trade cost between CEE and ROW	τ^{CR}	2.81		
Cost parameter for CEE offshoring	z^C	1.492		
Cost parameter for ROW offshoring	z^R	4.218		
Offshoring cost upper bound	j_{max}	1.5		
Region-dependent parameters	**Symbol**	**EUR**	**CEE**	**ROW**
Region size	n	0.23	0.05	0.72
Steady-state share of abstract labor	$\bar{N}_a$	0.385	0.361	0.235
Steady-state share of routine labor	$\bar{N}_r$	0.344	0.380	0.446
Steady-state share of manual labor	$\bar{N}_m$	0.271	0.259	0.319
Productivity level	Λ	1	1/2.4	1/8
Share of ICT capital	α_k	0.195	0.149	0.048
Share of routine labor	α_r	0.528	0.485	0.568
Share of the tradable sector	α_y	0.834	0.956	0.747
Trade deficit	Γ	-0.0004	0.0007	-0.0003
Openness to EUR goods	α_E		0.2314	0.0511
Openness to CEE goods	α_C	0.0121		0.0023
Openness to ROW goods	α_R	0.0168	0.0161	

[22] I remove the goods that are produced by and sold to the manufacturing sector from the calculation, as I considered them as offshoring and not final goods. Precise final good import shares over total demand are indicated in Appendix C.

4.2 Driving forces

Trade costs. I feed the model with a time-varying and exogenous measure of trade costs each period. This way, I can simulate a decrease in the costs of offshoring and in the trade of final goods. To obtain those costs, I use the ESCAP-World Bank (2020) bilateral-iceberg trade cost database based on Novy (2013). It gives the weighted average tariffs and non-tariffs costs – reported as $(\tau_t - 1) \times 100$ – between two countries annually for the manufacturing and agricultural sectors for most of the countries we are interested in.[23] Although tariffs were already quite low in 2000 between most countries, this database also takes into account all the costs associated with trade: administrative, transportation or communication costs for instance. I use the total trade cost only for the manufacturing sector to build these driving forces.

I adopt the following method to compute the average trade cost between two regions. First, I calculate a preliminary cost of import by region I from region J by averaging the import cost between each pair of countries i and j where i belongs to region I and j to region J. This average is weighted by the size of manufacturing imports by country i from country j, that I obtain from the WIOT.[24] Second, although the trade cost τ equals one inside a country, the regions of the model include several countries. Therefore, I need to divide the cost of imports of region I from region J by the trade cost internal to region I. This internal trade cost is computed using the same method, except that it is the weighted-average of the trade cost between each pair of countries i_S and i_R that both belong to I, and that i_S and i_R can be the same. This allows to also take into account the demand of domestic goods for which the trade cost is one. Finally, trade costs are considered symmetric in the literature and in the ESCAP-World Bank database. I follow this practice here. I compute the final trade cost between I and J as an average between the cost of import by I from J and the cost of import by J from I. This average is weighted by the sum of manufacturing imports of each region from the other. To sum up, the trade cost $\tau_t^{IJ} = \tau_t^{JI}$ between two different regions I and J equals:

$$\tau_t^{IJ} = \frac{\frac{\sum_{i\in I}\sum_{j\in J}\tau_t^{ij}Y_{T,t}^{ij}}{\sum_{i\in I}\sum_{j\in J}Y_{T,t}^{ij}}}{\frac{\sum_{j_S\in J}\sum_{j_R\in J}\tau_t^{j_Sj_R}Y_{T,t}^{j_Sj_R}}{\sum_{j_S\in J}\sum_{j_R\in J}Y_{T,t}^{j_Sj_R}}} \times \frac{\sum_{i\in I}\sum_{j\in J}Y_{T,t}^{ij}}{\sum_{i\in I}\sum_{j\in J}Y_{T,t}^{ij}+Y_{T,t}^{ji}} + \frac{\frac{\sum_{i\in I}\sum_{j\in J}\tau_t^{ji}Y_{T,t}^{ji}}{\sum_{i\in I}\sum_{j\in J}Y_{T,t}^{ji}}}{\frac{\sum_{i_S\in I}\sum_{i_R\in I}\tau_t^{i_Si_R}Y_{T,t}^{i_Si_R}}{\sum_{i_S\in I}\sum_{i_R\in I}Y_{T,t}^{i_Si_R}}} \times \frac{\sum_{i\in I}\sum_{j\in J}Y_{T,t}^{ji}}{\sum_{i\in I}\sum_{j\in J}Y_{T,t}^{ij}+Y_{T,t}^{ji}} \tag{70}$$

with $I, J = \{E, C, R\}$, $I \neq J$ and $Y_{T,t}^{ij}$ the total manufacturing imports by j from i.

For the year 2000, the starting value for the analysis, I obtain the following values of trade costs: $\tau^C = 1.60$ between EUR and CEE, $\tau^R = 2.02$ between EUR and ROW and $\tau^{CR} = 2.81$ between CEE and ROW. The evolution of these trade costs between 2000 and 2016 are shown in Appendix C in Figure 9. Trade costs are characterized by a decreasing trend during the period. The cost surplus due to trade is more than divided by two between EUR and CEE. This is notably the

[23] Data are not available for all years for The Netherlands, Hungary and Estonia, as such those countries are removed from the average calculation.

[24] As data after 2014 are not available in the WIOT, I use the manufacturing data of 2014 for 2015 and 2016.

consequence of the entry of Central and Eastern European countries in the European Union in 2004 and 2007. Costs also strongly decrease for trade with the ROW region, especially with the entry of China in the World Trade Organization in 2001.

ICT-capital prices. Second, I use the decrease in ICT-capital prices to model the increase in ICT-capital stocks. ICT-capital prices, investment and stock are available in the EU KLEMS database for most European Union countries (see Van Ark and Jäger (2017)).[25] I take from the database the prices of computing equipment, communication equipment, and computer software and databases. First, I compute an average ICT-capital price per country by weighting the prices of each of the three types of ICT capital by its corresponding stock. Then, to compute the price average for the EUR and the CEE regions, I weight the average price per country by the total ICT-capital stock of the corresponding country. Furthermore, I need to take into account the general inflation on the prices of all goods in each region. To do so, I use a country index of production price with the year 2000 as basis. To compute the regional price index, I weight the price of each country of the region by its gross value added. Finally, I divide the previously computed ICT-capital price by the production price index for each region. To sum up, the relative ICT-capital price index $P^J_{k,t}$ for region J is defined as:

$$P^J_{k,t} = \frac{\frac{\sum_{j\in J}\sum_{l\in L} P^j_{kl,t} K^j_{l,t}}{\sum_{j\in J}\sum_{l\in L} K^j_{l,t}}}{\frac{\sum_{j\in J} P^j_{V,t} V^j_t}{\sum_{j\in J} V^j_t}} \tag{71}$$

with V^j_t the gross value added in volume of country j belonging to region J, $P^j_{V,t}$ its associated price equals to 1 in 2000 and $P^j_{kl,t}$ the price of ICT-capital of type $l \in L$ in country j.

Details of the ICT-capital price movements for the EUR and CEE regions between 2000 and 2016 are presented in Figure 10 in Appendix C. For both regions, those prices fall until 2008, decreasing by around 30%. However, on the second half of the period, the decrease slows down for the EUR region and prices even stagnate for the CEE region. Finally, as no data is available for the ROW region, I consider that there is no change in ICT-capital price in that region in the baseline model.[26]

5 Historical analysis

The objective of this section is to study the role of automation and international trade on the structural dynamics of employment distribution in Western Europe between 2000 and 2016. First,

[25] Data are not available for Belgium, Bulgaria, Hungary, Poland and Romania for all or some years. Those countries are not included in the calculation. As such, some of the main countries of the CEE region are not included. However, the ICT-capital price in the CEE region has little influence on the employment dynamics in the EUR region which is the main focus of this paper. Therefore, the estimation I obtain for the ICT-capital price in the CEE region is sufficient considering the objective of the paper.

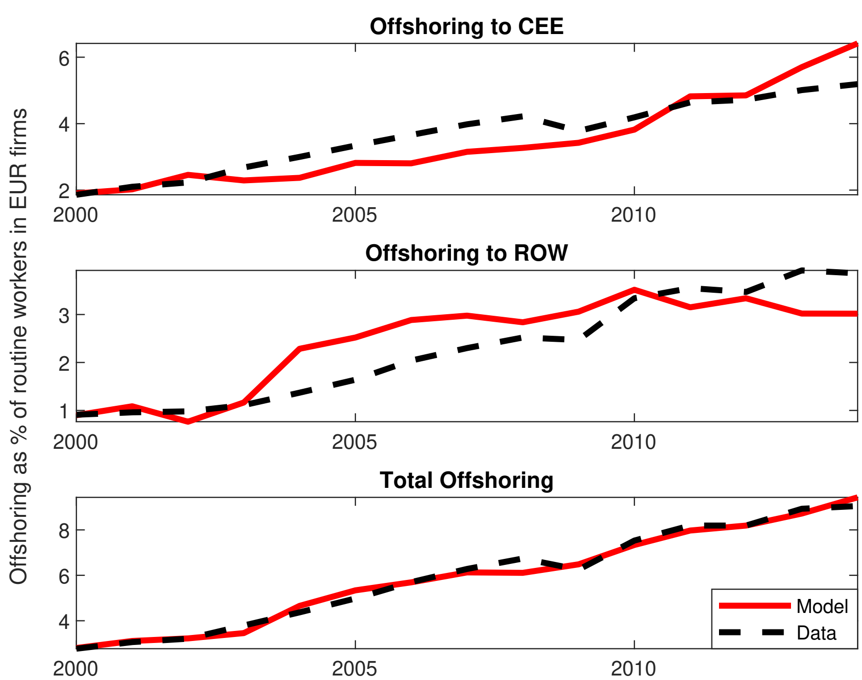
[26] As a robustness check, I also look at the dynamics of the model if I consider that the price of ICT capital in the ROW region follows the same dynamics as the one in the CEE region. I show in Figure 13 in Appendix E.1 that it has no effect on the main variables of interest.

I look at the predictions of the baseline model. Then, I run some counterfactual analyses to understand the precise role of each driving force on the changes of employment distribution. Finally, I conduct a welfare exercise to study the consequences of those changes on aggregate well-being.

5.1 Predictions of the baseline model

The model is solved using perfect-foresight non-linear simulations in Dynare (see Adjemian et al. (2011)). First, Figure 5 compares the offshoring dynamics produced by the model with the data between 2000 and 2014. To obtain the data, I apply the method explained in the previous section, using the WIOT. Unfortunately, data is not available after 2014. As we can observe, the model replicates very precisely the offshoring pattern of Western European firms. The levels of offshoring to CEE and ROW are very close to the data although there are a bit more volatile. In the middle of the period, offshoring to the ROW region is slightly overestimated while offshoring to CEE is a bit underestimated. However, more importantly, total offshoring is almost perfectly estimated for the whole period. This validates my modeling strategy for offshoring decisions and insures that offshoring occurs at an empirically realistic pace in the model, which can matter for the dynamics of the distribution of employment.

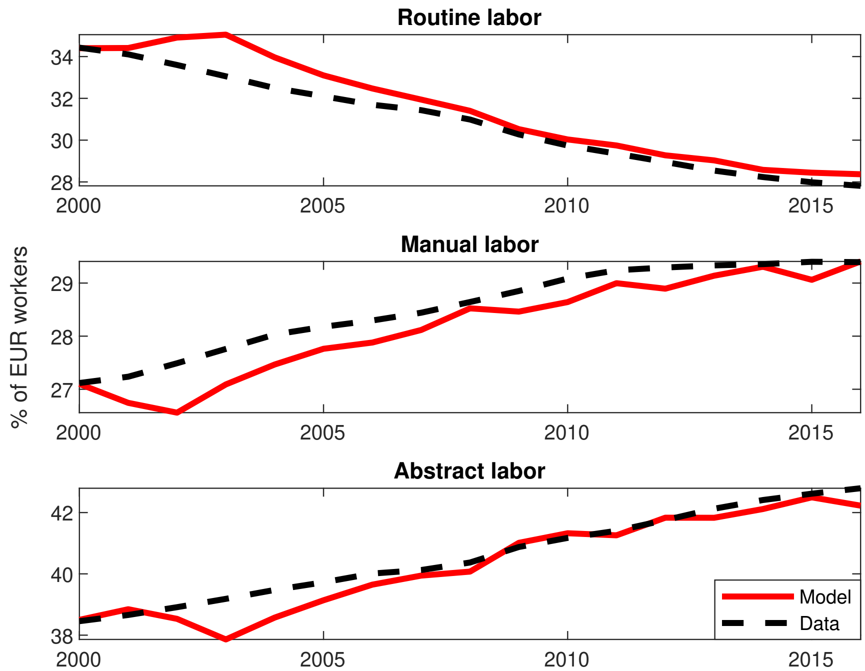
Figure 5: Offshoring dynamics



My main results are shown in Figure 6. It reports the changes in terms of the occupational distribution of employment for Western European countries both in the model and in the data.

The model does a very good job at replicating the typical polarization of employment. The fall of the routine labor share is well depicted: it drops from 34.4% to 28.4% of the non-agricultural labor force in the model while it falls from 34.4% to 27.8% in the data. The increase in the abstract labor share is also well reproduced. It goes from 38.5% to 42.2% in the model while it reaches 42.8% in the data. Finally, the rise of the share of manual workers is perfectly replicated: it increases from 27.1% to 29.4% both in the model and the data.

Figure 6: Employment dynamics



These dynamics can be understood through the lens of the model. Both driving forces imply a fall in the amount of domestic routine workers. First, the decrease in ICT-capital prices leads firms to increase automation by building up the stock of ICT capital and substitute routine workers with machines. Second, the fall of trade costs lowers the cost of offshored labor. Therefore, EUR firms replace domestic routine workers by routine workers of the other regions. As such, less workers train to perform routine tasks in the EUR region and more workers have to supply manual tasks. Finally, as ICT capital and abstract workers are relative complements, the increase in the stock of ICT capital raises the share of abstract labor. Now that I have shown that my model is able to replicate the observed polarization of labor markets in Western European countries, I look at the impact of the driving forces separately to precisely understand which is the key factor in explaining the observed changes in the distribution of employment.

5.2 Counterfactual analysis

As a counterfactual exercise, I make the model run with only one driving force at a time. Figure 7 and Table 2 show the distinct roles of automation and international trade on the dynamics of the occupational distribution of employment in Western Europe. As we can see, the decrease in the ICT-capital price is the main factor explaining the polarization of employment in the model. It explains the totality of the rise in high-skill workers supplying abstract tasks. A small effect coming from the increase in final good trade was to be expected. Indeed, the fall of trade costs dampens the price of the tradable good produced by EUR firms. As such, the demand for their good should rise and have a small positive effect on both abstract and routine workers producing this good. But, I show in Appendix D that, due to the relatively low level of final good trade between the three regions, it has almost no impact on the changes of the employment distribution. The exogenous dynamics of trade costs only modify the employment distribution through offshoring decisions, which has no impact on the share of abstract labor. As such, only automation has an up-skilling effect in the model, driving more individuals to train to become high-skill workers. Nevertheless, offshoring has some impact on the changes in the shares of manual and routine workers, as expected. But, this impact is quantitatively much lower than the effect coming from automation. Indeed, the decrease in the routine labor share due to the fall of ICT-capital price is 4.4 times higher than the decrease caused by the fall of trade costs (-4.99 percentage points versus -1.13pp). Finally, automation has an impact on the rise of the share of manual labor that is 25% higher than the effect of international trade.

Table 2: Employment changes in the data and different models

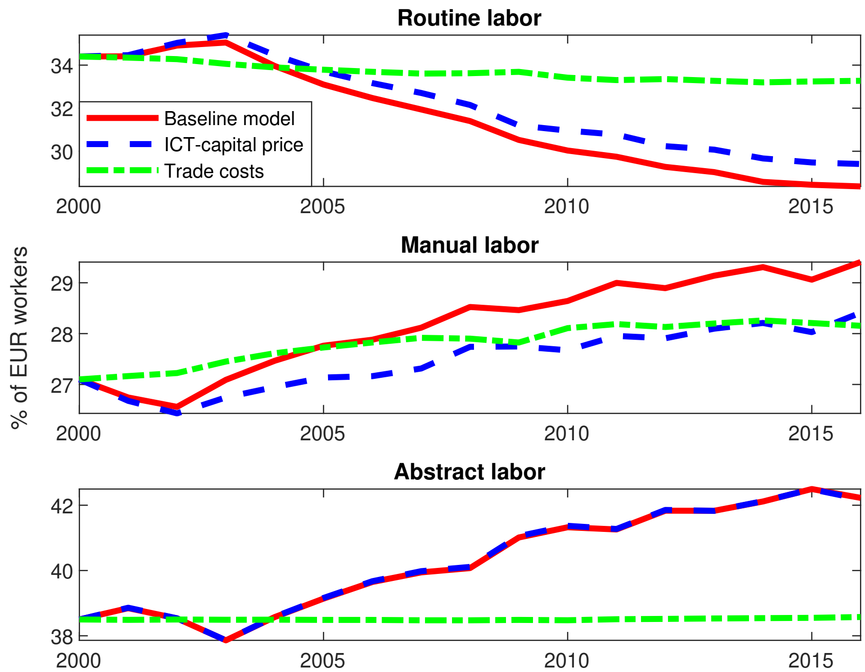
	Data	**Baseline**	**ICT capital**	**Trade**
Routine	-6.61	-6.03	-4.99	-1.13
Manual	2.28	2.31	1.31	1.05
Abstract	4.33	3.72	3.68	0.07

Results are expressed in percentage point variation.

The fact that automation is the main factor of labor polarization is consistent with several empirical studies focusing on Western Europe. For instance, Michaels et al. (2014) find that automation has a large influence on the decrease in routine labor and the increase in abstract labor in nine Western European countries. Similarly, Goos et al. (2014) consider that automation has a much bigger influence on job polarization than offshoring. Other papers consider that the effect of automation on labor polarization is small (see Cortes et al. (2017) and Eden and Gaggl (2018)) or that offshoring is its main driver (see Mandelman and Zlate (2021)).

Some reasons may explain those differences. First, the time period and the region of interest are different. Most of those papers study the United States and go back to the 1980s. Besides, theoretically, Mandelman and Zlate (2021) follow a different modeling strategy for the offshoring

Figure 7: Impact of each driving force on employment dynamics



process. Only high-skill individuals offshore their work to the other country. When trade costs diminish, some middle-skill workers become productive enough to offshore their own production and become considered high-skill (abstract) workers. Therefore, the fall of the trade cost directly causes an increase in abstract labor. This easily explains why they find that offshoring has a strong impact on the increase in the share of abstract labor and I do not. As previously explained, my modeling strategy makes more sense in the context of Western European countries. Indeed, offshoring to high-income countries mostly occurs within Western Europe and, as such, should not influence the aggregate distribution of employment in the region.

Finally, the value of the elasticity of substitution between routine and abstract workers has an impact on the results. Very different estimates have been given for this elasticity (see Hamermesh and Grant (1979) or Borjas et al. (2011)). The choice of $\theta = 5$ provides the best fit in the context of my model but is somewhat higher than most recent estimates. However, at least two reasons may account for this need of a higher value. First, ICT capital is the only type of capital in the model. However, ICT capital actually represents a small share of the total capital stock. An underestimated share of aggregate capital should imply a higher value of θ, as indicated in Hamermesh and Grant (1979). Second, estimates are usually done using aggregates, neglecting the presence of any "exterior" type of labor. However, here, low-skill manual workers are also present in the model. As such, there is an outside option available if the number of workers supplying routine labor is not large enough. The presence of this outside option for labor is the main justification provided by Blankenau and Cassou (2011) to explain why they find higher estimates when looking at each industry's elasticity instead of the aggregate elasticity for instance.

Nevertheless, as a robustness check, I show the consequences of choosing $\theta = 2.78$ in Appendix E.2 as recently estimated in Harrigan et al. (2021) for France. With this new value of θ, the capacity of the model to reproduce the exact dynamics of the shares of each type of labor somewhat diminishes although the qualitative results are unchanged. While the dynamics of the manual labor share remains very similar, the magnitude of changes of abstract and routine labor shares are lower. Here, the routine labor share falls from 34.4% to 30.3% while it drops to 28.4% in the baseline model. Besides, the abstract labor share increases from 38.5% to 40.4% while it reaches 42.2% in the baseline model. These differences are not surprising as the elasticity of substitution between ICT capital and routine labor is lower. The increase in automation remains the main factor of job polarization. Nevertheless, both its absolute and relative effects are dampened and the role of international trade is slightly magnified.

5.3 Welfare analysis

Finally, I investigate the welfare effects of a joint fall in ICT-capital prices and trade costs. This study is somewhat limited, as agents pool their income and are therefore insured against adverse shocks. Any redistributive effects are thus shut down by definition. However, the magnitude and direction of aggregate welfare changes still matter, especially in light of the ability of the model to reproduce the dynamics of the occupational distribution of employment between 2000 and 2016.

To determine the welfare consequences of both driving forces for the EUR region, I calculate the Hicksian-equivalent consumption change implied by the simulation over the 17 years. The Hicksian-equivalent change measures during T periods the percentage of permanent per-capita consumption ξ that the large family would have to lose – or gain – to be indifferent between the situation where ICT-capital prices and trade costs remain constant over the period and the situation where ICT-capital prices and trade costs decrease as in the data:

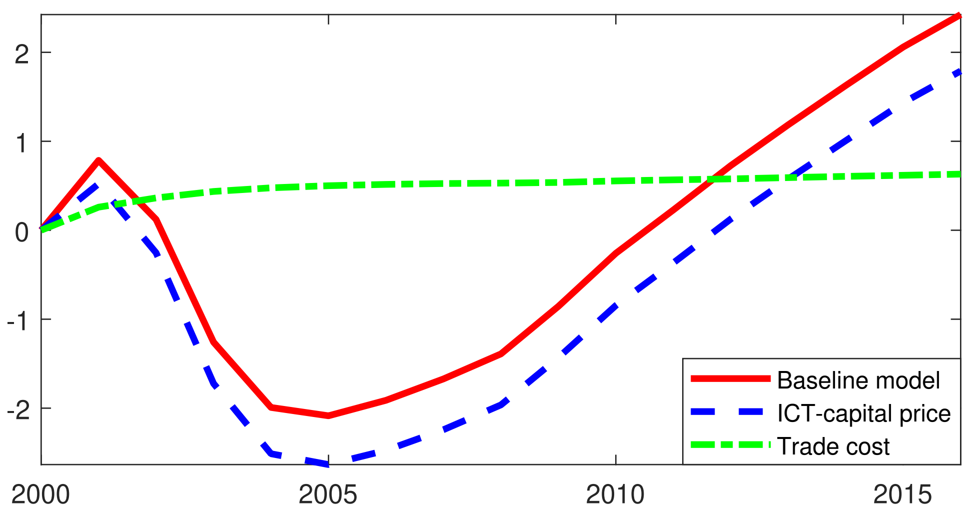
$$E_{2000} \sum_{t=2000}^{2016} \beta^t \Big[u\big((1-\xi)C_t\big)\Big] = \sum_{t=2000}^{2016} \beta^t \Big[u(C_{2000})\Big] \tag{72}$$

As such, it is a measure of aggregate cumulative welfare gains or losses for Western European countries. I present the welfare impact of both driving forces when they happen simultaneously or separately in Figure 8.

First, Figure 8 shows that 16 years of a fall of ICT-capital prices and trade costs had a positive effect in terms of cumulative welfare. Those driving forces increased aggregate per-capita consumption by almost 2.5% over the period. However, until 2011, the cumulative effects were negative. Indeed, the unexpected fall of the price of ICT capital has a negative short-term effect on consumption. When the first "shock" occurs, the family decides to decrease consumption and investment to increase the number of individuals that train to become high-skill workers, leading to a decrease in welfare in the short run. However, having more high-skill workers causes a rise of the average wage. As such, consumption starts increasing after a few periods. As welfare gains are discounted over time, cumulative welfare becomes positive only in 2011. Despite this short-term negative impact, almost 75% of the welfare gains over the period are due to the increase in automation.

Indeed, the fall in trade costs has a much smaller impact on welfare as it has a lower effect on the dynamics of employment distribution. However, its welfare impact is positive over the whole period. The fall in trade costs causes a decrease in the marginal cost of the tradable good as more tasks are offshored and supplied at a lower cost, leading to a decrease in its price. Furthermore, the price of foreign final goods also diminishes with the decrease in trade costs. As such, consumption increases despite the fact that the rise in offshoring forces some routine workers to become manual workers and to experience a fall of their wage.

Figure 8: Cumulative welfare changes for different scenarios



Welfare results are expressed in percentage of cumulative per-capita EUR consumption.

6 Conclusion

In this paper, I study the role of automation, final good international trade and offshoring on the changes of the occupational distribution of employment in Western Europe between 2000 and 2016. I build a three-region general equilibrium model where Western European firms can offshore routine production to the other regions of the world or replace routine labor by machines. I use actual annual changes in ICT-capital price and trade costs as exogenous driving forces to reproduce the dynamics of automation, offshoring and trade in final goods. The model accurately reproduces the polarization of employment that occurred during the period: the share of routine labor falls while the shares of abstract and manual labor increase.

Decomposing the effects of both driving forces, I find that automation is the overwhelming factor explaining the changes in the distribution of employment. Offshoring has a small effect on routine and manual labor shares, but none on the share of abstract labor. Furthermore, international trade in final goods has almost no impact, as its level remains relatively low. Finally, conducting a welfare analysis, I find positive cumulative welfare changes in the long run but short-run losses. Most of those variations are due to automation: the boom in high-skill training lowers consumption in the short term but raises it in the long run. The increase in international trade leads to lower but always positive welfare effects as it causes a decrease in the relative price of tradable goods.

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A Classification of labor

Table 3 indicates to which types of occupations are associated abstract, routine and manual labor for the EUR and CEE regions. For those regions, I use the two-digit ISCO-08 classification from the CEDEFOP. Abstract labor is composed of the high-skill occupations as usual in the literature. Then, occupations are separated between routine and manual labor following logic and the classification work done by Goos et al. (2014). Occupations with high offshorability and routine task intensities are considered as routine tasks. On the contrary, occupations with low offshorability and routine task intensities are classified as manual tasks.

Table 3: Separation of occupations into abstract, routine and manual labor

	Abstract Labor
1.	Legislators, senior officials and managers
2.	Professionals
3.	Technicians and associate professionals
	Routine Labor
41.	General and keyboard clerks
42.	Customer services clerks
43.	Numerical and material recording clerks
44.	Other clerical support workers
71.	Building and related trades workers, excluding electricians
72.	Metal, machinery and related trades workers
73.	Handicraft and printing workers
74.	Electrical and electronic trades workers
75.	Food processing, wood working, garment and other craft and related trades
81.	Stationary plant and machine operators
82.	Assemblers
93.	Labourers in mining, construction, manufacturing and transport
	Manual Labor
51.	Personal service workers
52.	Sales workers
53.	Personal care workers
54.	Protective services workers
83.	Drivers and mobile plant operators
91.	Cleaners and helpers
94.	Food preparation assistants
95.	Street and related sales and service workers
96.	Refuse workers and other elementary workers

The categories are those of the International Standard Classification of Occupation (ISCO-08). The categories "0. Armed forces" which is military as well as "6. Skilled agricultural and fishery workers" and "92. Agricultural, forestry and fishery labourers" which are composed of agricultural workers are not included in the computations.

For the ROW region, homogenized data at the two-digit level are not available. As such, I must use the ILO estimate of the shares for the one-digit ISCO-08 classification. In this classification, categories "6. Skilled agricultural and fishery workers" and "9. Elementary occupations" cannot be distinguished. I choose not to include them in the computation. As such, some workers that should be included are not. However, they are mostly manual workers and their impact on the employment distribution in the EUR region, which is the main concern of this paper, should be extremely limited. The separation of occupations into the three categories is detailed in Table 4.

Table 4: Separation of occupations for the ROW region

Abstract Labor	
1.	Legislators, senior officials and managers
2.	Professionals
3.	Technicians and associate professionals
Routine Labor	
4.	Clerical support workers
7.	Craft and related trade workers
8.	Plant and machine operators and assemblers
Manual Labor	
5.	Services and sales workers

The categories are those of the International Standard Classification of Occupation (ISCO-08). The categories "0. Armed forces", "6. Skilled agricultural and fishery workers" and "9. Elementary occupations" are not included in the computations.

B Definition of the different demands for tradable goods

$$
\begin{aligned}
y_{E,t}^{E} &= \alpha_y \left(\frac{P_{H,t}}{P_t}\right)^{-\rho} (1-\alpha_C-\alpha_r)\left(\frac{P_{T,t}}{P_{H,t}}\right)^{-\phi} (C_t+I_t) \\
y_{E,t}^{C} &= \alpha_y^{C} \left(\frac{P_{H,t}^{C}}{P_t^{C}}\right)^{-\rho} \alpha_E^{C}\frac{n^C}{n}\left(\frac{\tau_t^{C} P_{T,t}}{e_t^{C} P_{H,t}^{C}}\right)^{-\phi} (C_t^{C}+I_t^{C}) \\
y_{E,t}^{R} &= \alpha_y^{R} \left(\frac{P_{H,t}^{R}}{P_t^{R}}\right)^{-\rho} \alpha_E^{R}\frac{n^R}{n}\left(\frac{\tau_t^{R} P_{T,t}}{e_t^{R} P_{H,t}^{R}}\right)^{-\phi} (C_t^{R}+I_t^{R}) \\
y_{C,t}^{C} &= \alpha_y^{C} \left(\frac{P_{H,t}^{C}}{P_t^{C}}\right)^{-\rho} (1-\alpha_E^{C}-\alpha_R^{C})\left(\frac{P_{T,t}^{C}}{P_{H,t}^{C}}\right)^{-\phi} (C_t^{C}+I_t^{C}) \\
y_{C,t}^{E} &= \alpha_y \left(\frac{P_{H,t}}{P_t}\right)^{-\rho} \alpha_C\frac{n}{n^C}\left(\frac{\tau_t^{C} e_t^{C} P_{T,t}^{C}}{P_{H,t}}\right)^{-\phi} (C_t+I_t) \\
y_{C,t}^{R} &= \alpha_y^{R} \left(\frac{P_{H,t}^{R}}{P_t^{R}}\right)^{-\rho} \alpha_C^{R}\frac{n^R}{n^C}\left(\frac{\tau_t^{CR} e_t^{C} P_{T,t}^{C}}{e_t^{R} P_{H,t}^{R}}\right)^{-\phi} (C_t^{R}+I_t^{R}) \\
y_{R,t}^{R} &= \alpha_y^{R} \left(\frac{P_{H,t}^{R}}{P_t^{R}}\right)^{-\rho} (1-\alpha_C^{R}-\alpha_E^{R})\left(\frac{P_{T,t}^{R}}{P_{H,t}^{R}}\right)^{-\phi} (C_t^{R}+I_t^{R}) \\
y_{R,t}^{C} &= \alpha_y^{C} \left(\frac{P_{H,t}^{C}}{P_t^{C}}\right)^{-\rho} \alpha_R^{C}\frac{n^C}{n^R}\left(\frac{\tau_t^{CR} e_t^{R} P_{T,t}^{R}}{e_t^{C} P_{H,t}^{C}}\right)^{-\phi} (C_t^{C}+I_t^{C}) \\
y_{R,t}^{E} &= \alpha_y \left(\frac{P_{H,t}}{P_t}\right)^{-\rho} \alpha_R^{E}\frac{n}{n^R}\left(\frac{\tau_t^{R} e_t^{R} P_{T,t}^{R}}{P_{H,t}}\right)^{-\phi} (C_t+I_t)
\end{aligned}
$$

C Data and model

Table 5: Share of import or domestic demand by region of origin

	EUR	**CEE**	**ROW**
EUR	99.21%	9.39%	1.11%
CEE	0.40%	90.33%	0.03%
ROW	0.39%	0.28%	98.86%

Each row indicates the origin of products while each column indicates its destination. Results are indicated as a share of total goods in the receiving region. As such, each column sums up to 100%.

Figure 9: Trade cost between the different regions

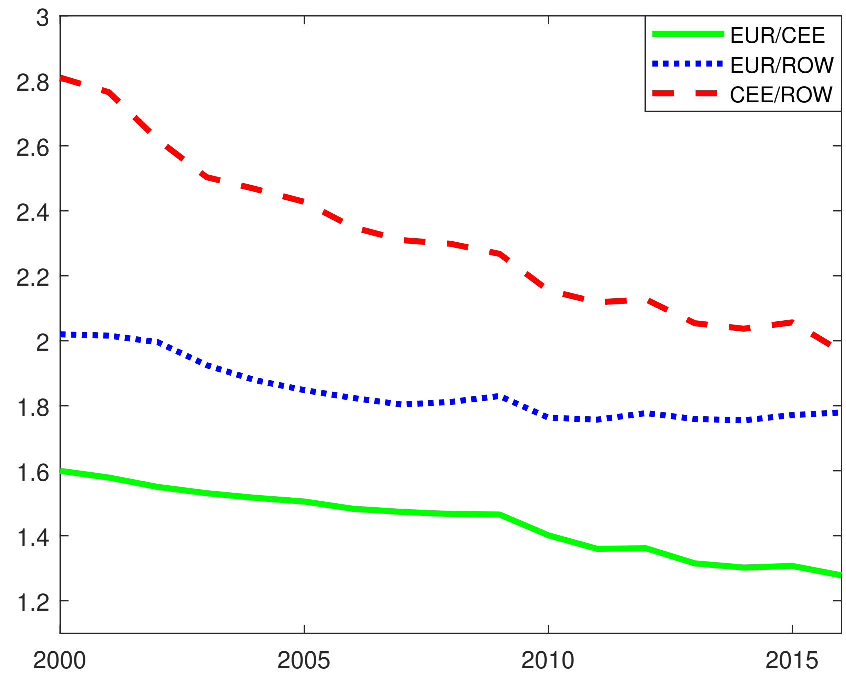


Figure 10: ICT-capital cost (normalized to 1 en 2000)

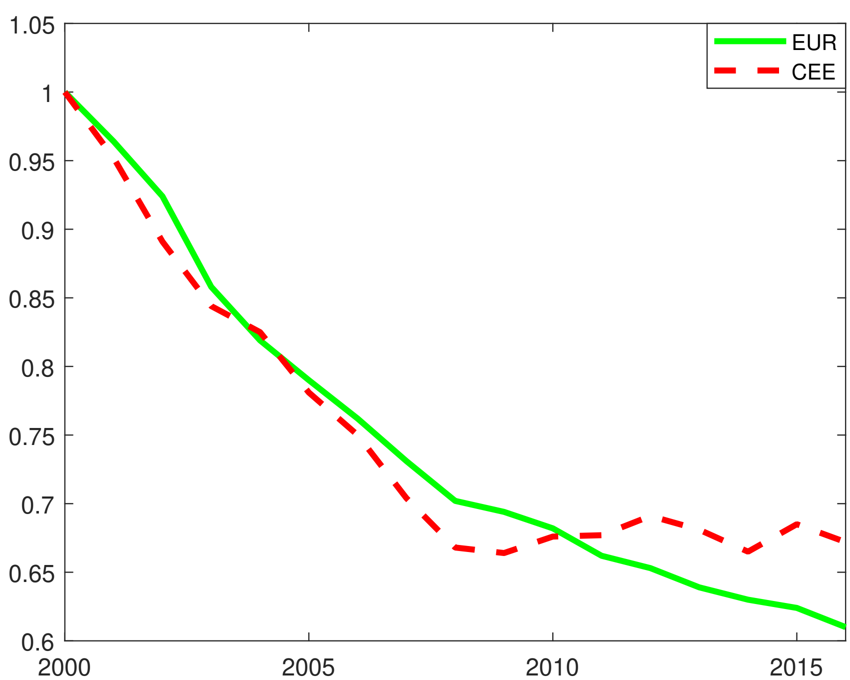
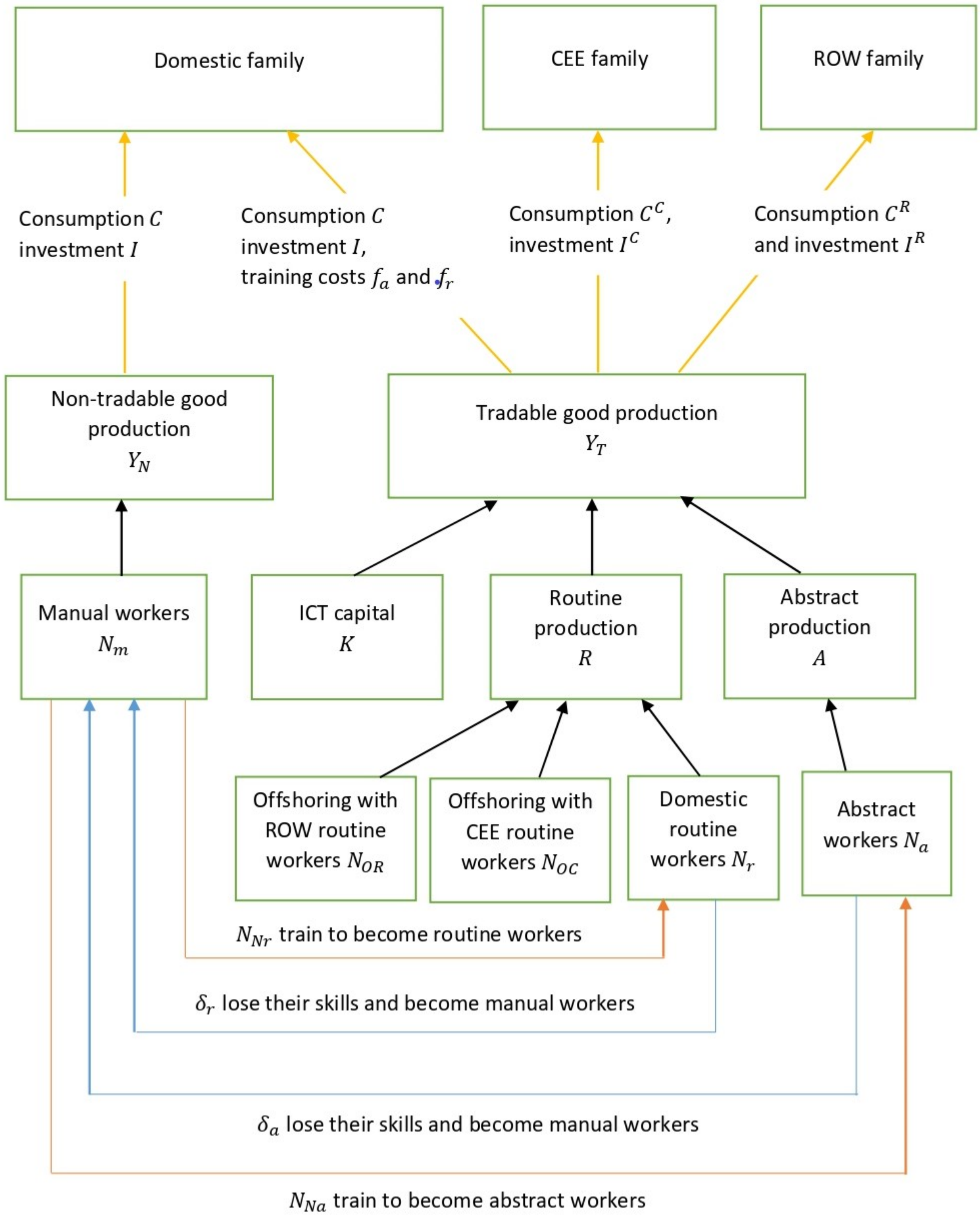


Figure 11: General presentation of the Model



D Detailed trade cost impact on employment dynamics

I separate the impact of the decrease in trade costs on the dynamics of employment between the impact of offshoring and the one of trade on final goods. Figure 12 shows the results. As we can see, the trade of final goods has almost no impact. The decrease in the trade costs leads to a small increase in the demand of EUR goods abroad. As such, EUR tradable-good firms increase their production which causes a slight increase in the number of both routine and abstract workers. But, as international trade is very low between the EUR region and the other regions displayed in the model, this effect is extremely small. Thus, almost all changes in the distribution of employment due to the decrease in trade costs come from offshoring. That is why I focus on offshoring and not final good trade in the main part of the paper.

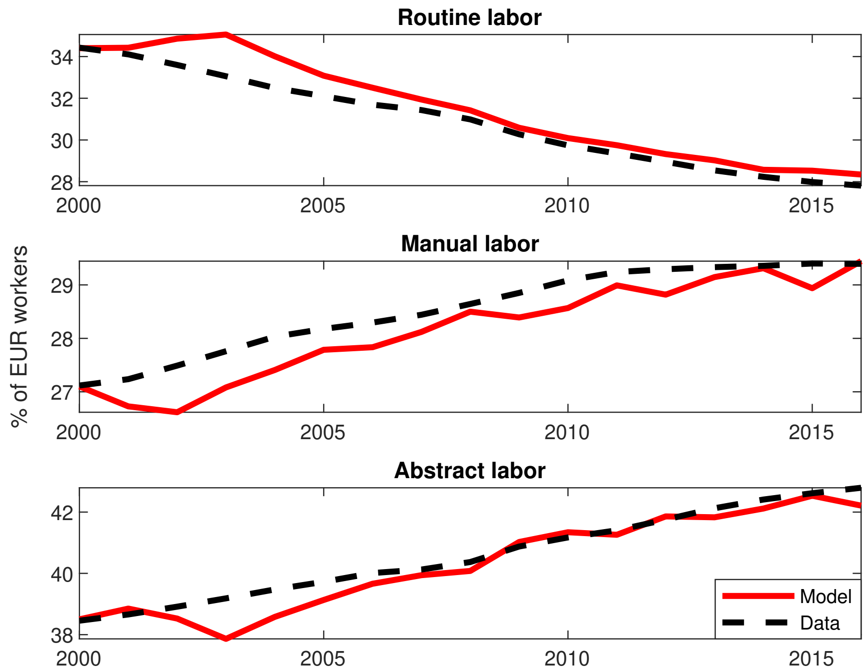
Figure 12: Impact of each type of trade on the employment distribution

E Robustness check

E.1 Changes in ICT-capital prices in the ROW region

Figure 13 shows the employment dynamics when the ROW region is subjected to the same ICT-capital price exogenous driving force as the CEE region. As we can see, the dynamics are exactly the same. This supplementary driving force has absolutely no effect on the labor dynamics in the EUR region.

Figure 13: Labor share dynamics with changing ICT-capital price in the ROW region



E.2 Employment dynamics when $\theta = 2.78$

Figure 14 shows the difference in the dynamics of employment between the baseline model and the model where the elasticity of substitution between abstract and routine labor is $\theta = 2.78$. Figure 15 indicates the impact of each driving force with this value of θ.

Figure 14: Comparison with the baseline model

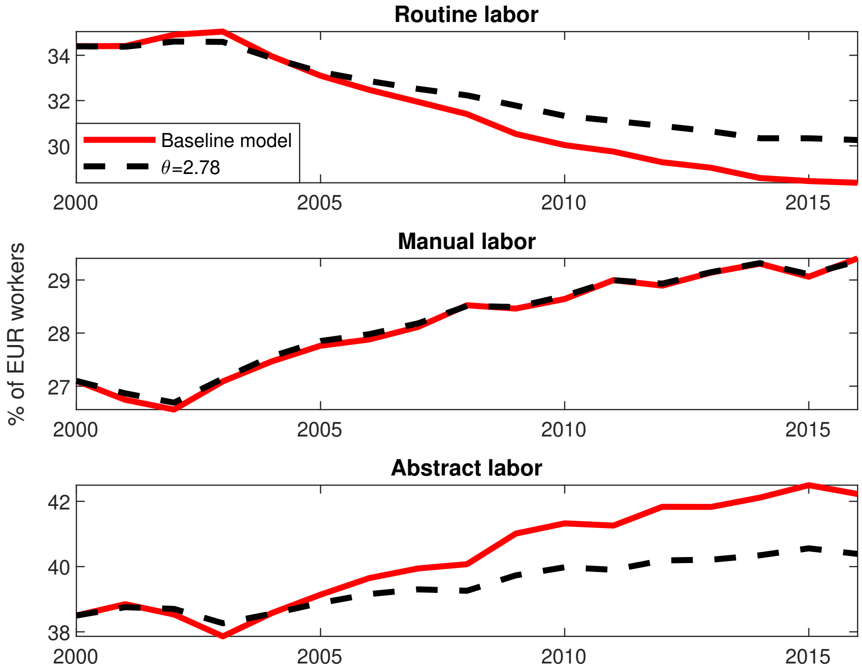
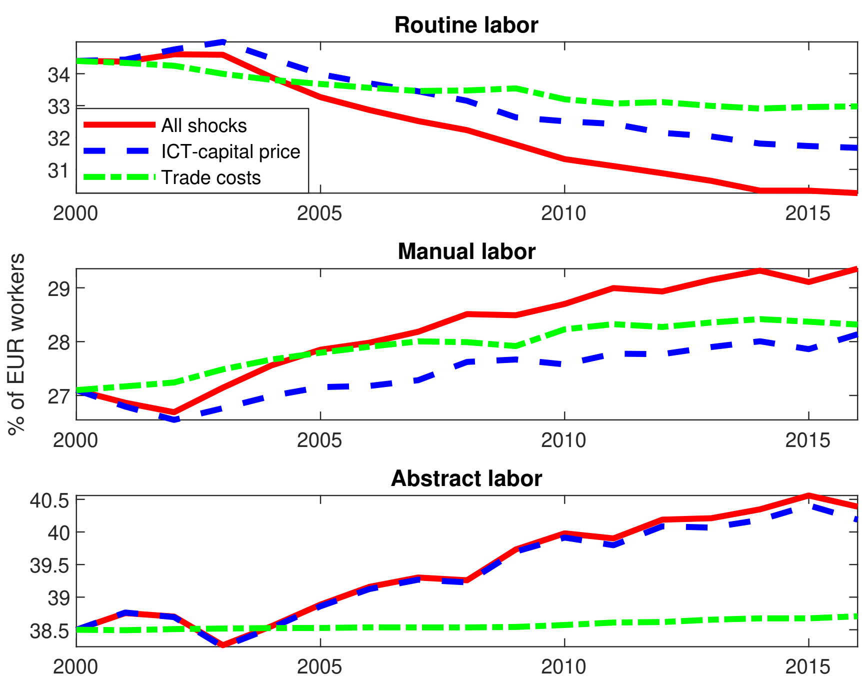


Figure 15: Impact of each driving force when $\theta = 2.78$



F Model and Results with offshoring CEE firms

F.1 Model

As a robustness check, I allow CEE firms to offshore routine tasks to the ROW region. In this case, the part of the model explaining the way routine tasks are supplied for CEE firms is modified. The same modeling strategy as for EUR firms is used, but with only one offshoring category.

CEE firms can employ domestic workers or ROW workers through offshoring. Both types of workers have the same production function when working for CEE firms. Each of them supplies the effort $l_t^C = r_t^C \Lambda_t^C x_{r,t}$. Domestic workers are paid the CEE routine wage expressed in real terms $w_{r,t}^C = W_{r,t}^C / P_{T,t}$ while ROW workers earn $w_{r,t}^R T_t^{CR}$, with $T_t^{CR} = e_t^{RC} P_{T,t}^R / P_{T,t}^C$ the terms of trade between countries CEE and ROW, and $e_t^{CR} = e_t^R / e_t^C$ the nominal exchange rate between the CEE and the ROW regions. Firms incur a supplementary cost to offshore labor $F_t^{CR}(j) = \zeta^{CR}(j)\tau_t^{CR}$ with $\zeta^{CR}(j) = z^{CR}(1 + j_{max}^C)$. As such, the costs to produce a specific task domestically $c_{D,t}^C$ and to offshore it to the ROW country $c_{OR,t}^C(j)$ are expressed as follows:

$$c_{D,t}^C = \frac{w_{r,t}^C}{x_r \Lambda_t^C} \tag{73}$$

$$c_{OR,t}^C(j) = F_t^{CR}(j) \frac{w_{r,t}^C T_t^{CR}}{x_r \Lambda_t^C} \tag{74}$$

This means that a task is offshored whenever

$$c_{D,t}^C \geq c_{OR,t}^C(j) \tag{75}$$

I need to assume that $c_{D,t}^C \geq c_{OR,t}^C(0)$ to make sure that at least some offshoring takes place. There is only one "marginal offshoring task" $j = J_{OR,t}$ such that $c_{D,t}^C = c_{OR,t}^C(J_{OR,t})$. As workers are perfectly substitutable, this means that for all tasks $j \geq J_{OR,t}$, routine tasks are produced domestically while for $j \leq J_{OR,t}$ they are produced through offshoring.
Perfect competition implies that the cost of each task is defined as follows:

$$c_t^C(i,j) = \begin{cases} c_{OR,t}^C(j) & = F_t^{CR}(j) \frac{w_{r,t}^R T_t^{CR}}{x_{r,t} \Lambda_t^C} & 0 \leq j < J_{OR,t} \\ c_{D,t}(j) & = \frac{w_{r,t}^C}{x_{r,t} \Lambda_t^C} & J_{OR,t} \leq j \leq j_{max}^C \end{cases}$$

The routine average marginal cost $mc_{r,t}(i) = mc_{r,t}$ can be expressed as the weighted average of the average cost of each type of workers:

$$mc_{r,t}^C(i) = G(J_{OR,t}) mc_{OR,t}^C + \left[1 - G(J_{DC,t})\right] mc_{D,t}^C \tag{76}$$

with the average (marginal) cost of a domestic worker and of a worker of the ROW region expressed respectively as:

$$mc^C_{D,t} = \frac{w^C_{r,t}}{x_{r,t}\Lambda^C} \tag{77}$$

$$mc_{OR,t} = \frac{1}{J_{OR,t}} \int_0^{J_{OR,t}} F^{CR}_{C,t}(j) \frac{w^R_{r,t} T^{CR}_t}{x_{r,t}\Lambda^C} \; dj \tag{78}$$

As the monopolistic firms choose the same price, they all follow the same decision process. The total of workers supplying routine tasks for the CEE firms is $N^C_{f,t} = N^C_{D,t} + N^C_{OR,t}$ with N^C_{OR} the amount of ROW workers and $N^C_{D,t}$ the amount of domestic workers supplying routine tasks for CEE firms.

We can express the shares of each type of workers over the number of workers producing routine tasks for EUR firms as:

$$\frac{N^C_{OR,t}}{N^C_{f,t}} = G(J_{OR,t}), \qquad \frac{N^C_{D,t}}{N^C_{f,t}} = 1 - G(J_{OR,t}) \tag{79}$$

Finally, given the assumption of uniform distribution, we can easily define the location decision cutoffs as:

$$J_{OR,t} = j^C_{max} \frac{N^C_{OR,t}}{N^C_{f,t}} \tag{80}$$

We also need to modify the expression of the number of workers supplying routine tasks in the ROW region:

$$N^R_{r,t} = \left(N^R_{D,t} + \frac{n}{n^R} N_{OR,t} + \frac{n^C}{n^R} N^C_{OR,t} \right) \tag{81}$$

Finally, the equations of international trade for the CEE and the ROW regions become:

$$n^C N^C_{OR,t} w^R_{r,t} T^{CR}_t \frac{P^C_{T,t}}{P^C_t} + n^R y^C_{R,t} S^{CR}_t + n \frac{y^C_{E,t}}{S^C_t} = n N_{OC,t} w^C_{r,t} \frac{P^C_{T,t}}{P^C_t} + n^C \left(y^E_{C,t} + y^R_{C,t} \right) + \Gamma^C \tag{82}$$

$$n \frac{y^R_{E,t}}{S^R_t} + n^C \frac{y^R_{C,t}}{S^{CR}_t} = \left(n N_{OR,t} w^R_{r,t} + n^C N^C_{OR,t} w^R_{r,t} \right) \frac{P^R_{T,t}}{P^R_t} + n^R \left(y^E_{R,t} + y^C_{R,t} \right) + \Gamma^R \tag{83}$$

F.2 Parametrization

Following the same method as previously, I obtain that the share of offshoring between CEE and ROW regions in 2000 is $\bar{G}(J_{OR}) = 1.1\%$. Two parameters are added to the model : z^{CR} and j^C_{max}. I choose the values to best follow the dynamics of offshoring between the CEE and ROW regions in the data. I obtain: $j^C_{max} = 7$ and $z^{CR} = 1.185$.

F.3 Results

Figure 16 shows the dynamics of the distribution of employment when offshoring between the CEE and ROW regions is allowed. As we can see, the results are extremely similar to the baseline model. The decrease of routine labor is almost perfectly depicted while the increase of both abstract and manual labor are also well reproduced.

Figure 16: Dynamics of the distribution of employment