Three Essays on Automation

Tommaso SANTINI

UNIVERSITAT AUTÒNOMA DE BARCELONA

DOCTORAL THESIS

Three Essays on Automation

Author:
Tommaso SANTINI

Supervisors:
Javier FERNÁNDEZ-BLANCO
Jordi CABALLÉ

A dissertation submitted in fulfillment of the requirements for the degree of Doctor of Philosophy in the International Doctorate in Economic Analysis (IDEA), Departament d'Economia i Història Econòmica.

May 12, 2021

Ad Angelina

Acknowledgements

I am extremely grateful to my advisors Javier Fernández-Blanco and Jordi Caballé for their guidance, support and patience. I am also indebted to Bruno Conte and Alessandro Ruggeri for having been my junior mentors during the Ph.D.

In writing this thesis, I benefited from the feedback of many kind people. I especially thank Árpád Ábrahám, Jesus Beuren, Christopher Busch, Dennis Hutschenreiter, Philipp Kircher, Matthias Kredler, Lars Ljungqvist, Joan Llull, Alexander Ludwig, Inés Macho-Stadler, Asier Mariscal, Francesc Obiols-Homs, David Pérez-Castrillo, Luis Rojas, Raul Santaeulalia-Llopis, Eugenia Vella, Ludo Visschers, and Hanna Wang.

I have been lucky to meet outstanding people during these years. I thank Daniele Angelini, Anna Houštecká, Federico Lucchesi, Davide Pietrobon and all the students of IDEA for the time and knowledge that they have shared with me.

A warm thanks to Àngels and Mercè, for their invaluable help from the first day I arrived at the Autònoma.

I thank my family, the Soprattutto and all my friends for the support and the conversations that have indirectly shaped this thesis.

A special thanks to Angelica for putting up with me all this time.

Thesis Outline

Recent advances in technological capabilities raise concern that a sizable fraction of today's occupations is at high risk of being automated in the near future. There are many studies in the literature arguing that this is a concrete possibility. What these papers do in practice is first to understand what technology is able to do today and what will be able to do in the near future according to technology experts. Then, they match this information with the tasks that are performed today by workers in their occupations. While there is a direct effect that tends to decrease the demand for such workers, there are other general equilibrium effects associated with the adoption of automation technology that tend to increase the demand for labor. Indeed, despite massive automation has happened in the past, labor did not become "redundant".

Despite the known benefit of technological progress on economic growth and living standard, it has also been identified as one of the major reasons for the decrease in the earning and employment prospects for specific groups of populations. To understand automation means to design better policies that can maximize the benefits of technological advances by incentivizing innovation and reallocating resources to the most fragile households. Moreover, the Coronavirus pandemic could further increase the incentive to adopt labor-substituting technologies, as machines do not get infected and sick. To understand the conditions that foster the adoption of automation technology and the overall effect of automation on earnings and employment is the focus of this doctoral thesis.

In Chapter 1, *"Automation with Heterogeneous Agents: the Effect on Consumption Inequality"*, I study the distributional implications on consumption of the adoption of automation technology. I combine an Aiyagari incomplete market model with educational choice and a task-based model of production. Workers that choose to get a college education develop skills with a higher degree of capital complementarity with respect to workers who do not get college education. As a consequence, the effect of automation impacts their earnings in a different way. On top of that, I consider the effect of automation on the return to wealth and show that it is key in determining the overall effect on consumption inequality. The fundamental idea is that automation has an effect on earnings but also on capital income. To study the effect of automation on consumption I argue that is important to consider the joint distribution of earnings and wealth. Indeed, as those who earn a higher salary are also able to accumulate more wealth, the increase in capital income amplifies the effect of automation on inequality. In a quantitative analysis, I calibrate the model to the US economy between 1978 and 1981. I compute the transitional dynamics from the initial steady state when I shock the economy with an increase in automation possibilities and the introduction of new tasks for labor, which I estimate from the data. I first show that the model is able to replicate closely the increase in consumption inequality from 1981 to 2007. Then, I decompose the role played by the various components in the model to highlight that the return to wealth channel and endogenous educational choice are crucial to understand the overall distributional effects on the consumption distribution.

Chapter 2, *"Automation and Sectoral Reallocation"*, is a joint work with Dennis Hutschenreiter and Eugenia Vella. We study the effects of automation in the form of robot adoption in Germany. Empirical evidence in the literature suggests that robot adoption has induced a sectoral reallocation of workers from the manufacturing to the service sector in the German economy, leaving total unemployment unaffected, in contrast with the negative effect in the United States. To rationalize this evidence, we develop a general equilibrium model with search and matching frictions, participation choice, and two production sectors. We calibrate the model for Germany and perform analysis across steady states. In the model, as in the German data, automation does not destroy existing jobs but induces firms to create fewer new vacancies in the robot-exposed sector (manufacturing) and job seekers to reallocate their search towards the non-exposed sector (services). We show indeed that aggregate employment is hardly affected.

What are the conditions in which it is more convenient to adopt new technologies? What are the factors that influence such a decision? In Chapter 3, *"Common Ownership and Automation"*, joint with Dennis Hutschenreiter, we investigate what is the effect of Common Ownership on the adoption of automation technology. By Common Ownership, we refer to institutional investors that own blocks of different public firms competing in the same product markets. We build a symmetric Cournot model with a task-based production side. We show that automation increases (decreases) with Common Ownership if the elasticity of the capital supply is smaller (larger) than the elasticity of the labor supply function in the industry.

Contents

Chapter 1

Automation with Heterogeneous Agents: the Effect on Consumption Inequality

Abstract

In this paper, I study technological change as a candidate for the observed increase in consumption inequality in the United States. I build an incomplete market model with educational choice combined with a task-based model on the production side. I consider two channels through which technology affects inequality: the skill that an agent can supply in the labor market and the level of capital she owns. In a quantitative analysis, I show that (i) the model replicates the increase in consumption inequality between 1981 and 2008 in the US (ii) educational choice and the return to wealth are quantitatively important in explaining the increase in consumption inequality.

1.1 Introduction

Since the beginning of the eighties, consumption inequality in the United States has risen.[1] The increase ranges, between 1982 and 2005, from around 30% to 95%, depending on the adopted measure.[2] In this paper, I evaluate the role played by technological change and, in particular, by the automation of tasks, in the observed increase in consumption inequality.

To this end, I build a general equilibrium model combining two theoretical frameworks. On the household side, I use an Ayiagari incomplete market model with educational choice while, on the production side, I use a task-based model borrowed from Acemoglu and Restrepo, 2018. Agents face skill-specific uninsurable idiosyncratic risk and choose how much to save and consume. When they die, they are replaced by their offspring who can decide whether to go to college or not. A unique final good is produced by aggregating a unit measure of tasks. Three inputs of production, capital, unskilled labor, and skilled labor are endogenously allocated to perform tasks, given their productivities and endogenous factor prices.

Automation directly displaces low-skill workers from the performance of some tasks and increases aggregate productivity. The net effect on the wage of the low-skill workers depends on the trade-off between the displacement and the productivity effect. Moreover, as high-skill workers perform tasks that cannot be performed by machines, automation increases the relative demand for skilled relative to unskilled workers (Acemoglu and Autor, 2011). I consider the effect of the introduction of new tasks in which labor has a comparative advantage, which has been argued to be one of the most important forces countervailing the displacement effect of automation.[3] In my model, the introduction of new tasks increases productivity and the demand for high-skill relative to low skill workers. The assumption that new tasks increase the relative labor demand of more educated workers receives support

[1] See Aguiar and Bils, 2015, Attanasio, Battistin, and Ichimura, 2004, Attanasio and Pistaferri, 2014, Attanasio and Pistaferri, 2016, and Heathcote, Perri, and Violante, 2010.

[2] Attanasio and Pistaferri, 2016 show that consumption inequality, measured as the variance of log-consumption, varies between 30% to 95%. The variation in this result depends on the different ways in which consumption is computed in the data.

[3] Automation technologies might need labor in order to be operated and this, directly, can create demand for new jobs (or new tasks for existing jobs). Moreover, by decreasing the relative price of labor with respect to capital, automation incentivizes the development of new, labor-intensive technologies. Acemoglu and Restrepo, 2019 show that the introduction of new tasks can account for around 50% of the employment growth in the US between 1980 and 2010. Over the same period, a 10 log points increase in labor demand is attributed to the introduction of new tasks.

from the data.[4]

Technological change affects labor demand and wages, but also the return to capital. In particular, the adoption of automation technology increases capital demand and, therefore, the return to wealth for the agents who lend capital to the firms. As wealth is unequally distributed among the agents, the increase in the price of capital has distributional implications. In this model, automation increases *total income* inequality for two different but interconnected reasons. First, because it increases labor income inequality due to differential ways in which technology impacts skill demands. Second, because it increases capital income inequality by raising the return to wealth. As agents who earn a higher salary are also able to accumulate more wealth, the rise in the return to wealth *increases* total income inequality.

The spread in the income distribution translates into increased consumption inequality. The mapping between these two depends on the aggregation of individual saving decisions of the agents. This, in turn, depends on the amount of risk agents face. I assume that labor income risk fluctuations depend on education, as this is the case in the data (Guvenen, 2009).

Crucially, I model educational choice to allow agents to react to prices changes by adjusting their skill supplies. To ignore this fact, the effect of automation on the education premium would be overestimated. Indeed, as the education premium reacts to scarcity, the education decision buffers the increase in the premium implied by technological change.

I calibrate the model to the US economy over the period between 1978 and 1981. With the calibrated model, I compute transitional dynamics to a new steady-state with different levels of technology. In particular, I show that, after an automation shock, the wage of workers without education decreases in the short run and recovers along with the transition. Despite the short-run decrease in the low-skill labor income, total income does not decline for every agent without education. Indeed, richer low-skill agents who had a positive series of labor income shocks can experience a rise in total income, as the increase in the return of capital compensates for the decline in labor income.

Thereafter, I estimate from the data measures of task automation and task introduction spanning from 1981 - the initial steady-state - to 2008. I plug these series in the model and compute the implied transitional dynamics. I

[4] Acemoglu and Restrepo, 2018 show that occupations with a greater number of new job titles employ, on average, workers with more years of schooling.

show that the estimated technological change explains the increase in consumption inequality observed in the US in the years under study. Moreover, the model explains around 35% of the increase in the college premium and around 53% of the increase in the share of workers with a college degree in the US. Finally, I estimate the role of various components in the model in explaining the increase in inequality. In particular, I show that both the return to wealth channel and the endogenous education decision are quantitatively important. To estimate the role played by the increase in the return to wealth, I compute the transition between steady-states with the interest rate fixed to its initial steady-state value. In this case, the effect of technological change on inequality is 4% lower as it increases only the education premium and it does not directly increase inequality in capital income. To quantify the role of endogenous educational choice, I compute the transition with the probability of dying equal to zero. In this way, the shares of educated and uneducated workers remain fixed to the initial steady-state value. With this decomposition, I show that without allowing the agents to adjust their skill supplies as the demand changes, the overall effect of technology on inequality is twice as large.

Literature Review

First, this paper contributes to the literature that focuses on the determinants of income and consumption inequality. There are several papers that use the Aiyagari, 1994, Bewley, 1986, and Huggett, 1993 framework to study the role of technology on inequality as, for instance, Heckman, Lochner, and Taber, 1998, Hubmer, Krusell, and Smith Jr, 2016, and Kaymak and Poschke, 2016. The most important differences with respect to these studies are the way in which I conceptualize technological change - a combination of automation and creation of new tasks - and that I consider the effect of the return to wealth on inequality. Methodologically, my paper is similar to Kaymak and Poschke, 2016 in the way I decompose the effect on consumption inequality of various channels in the model. Another paper that underlines the importance of the return to wealth is Moll, Rachel, and Restrepo, 2019. They combine a task-based model with a perpetual youth structure with imperfect dynasties, which is another way to get a determinate wealth distribution and study the implication of the return to wealth on inequality. Using instead an incomplete market model, I can account for differences in labor income risk between education groups (Guvenen, 2009). Another key difference with respect to that paper is that I do model educational choice, and I show that it is crucial in the observed increase in inequality. Finally, I also consider the effect of new tasks introduction.

Second, this paper contributes to the literature that studies the effect of automation, spurred by recent advances in technological capabilities. Like the majority of papers in this literature, I use a task-based model of production (Zeira, 1998, Acemoglu and Autor, 2011 and Acemoglu and Restrepo, 2018). Most of the papers studying the effect of automation using general equilibrium models either focus on aggregate labor demand (as Acemoglu and Restrepo, 2018) or consider labor income inequality (Hémous and Olsen, 2014). But as automation increases the demand for capital, I show that the channel through the increase in the return of wealth is quantitatively important. I extend the conceptual models used in previous research by including heterogeneous capital accumulation that depends on the labor income and individual risk. In a representative household model (e.g. Acemoglu and Restrepo, 2018) automation always increases total income and consumption. That is because automation always increases output; hence, even if wages are reduced, the household is compensated with a higher capital income. This is not true for all the agents in a model with endogenous wealth distribution.

The rest of the paper is organized as follows: In Section 1.2 I explain the structure of the model. In Section 1.3.1 I take the model to the data. In Section 1.3.2 I discuss the mechanisms of the model. In Section 1.3.3 I explain the estimation of the shocks that I use in Section 1.3.4 to contrast the model with the data. In Section 1.3.5 I quantify the role of various elements of the model. Section 1.4 concludes.

1.2 Model

The model combines two theoretical frameworks. The consumption side borrows the basic features of Aiyagari (1994) incomplete market model combined with endogenous educational choice. The production process, instead, is modeled with a particular task-based production function borrowed from Acemoglu and Restrepo, 2018.

The population is normalized to one and time is discrete and indexed by t. I make the dependence of time explicit to underline non-stationarity in the model. An agent is born with a level of assets and chooses whether or not to become high skill by paying a cost $\theta(a)$ which is a function of asset holdings. This decision is permanent for an agent. Then, during her life, the agent chooses how much to save and how much to consume; she cannot borrow, and her labor supply is exogenous. In every period there is a probability of dying d; when an agent dies, her offspring inherits the level of asset holdings the agent had in her last period of life.

Productivity differs between skill groups but is identical within each skill group. Consequently, wages differ between skills but are identical within skills. On top of this, agents face a not insurable idiosyncratic shock and this creates heterogeneity within each skill group.

Consumption Side:

The initial problem of an agent is the following:

$$v_t^n(a) = \max\left\{\mathbb{E}_{\varepsilon^h}\left\{v_t^h(a,\varepsilon^h)\right\} - \theta(a),\quad \mathbb{E}_{\varepsilon^\ell}\left\{v_t^\ell(a,\varepsilon^\ell)\right\}\right\}, \tag{1.1}$$

where $v_t^n(a)$ is the value function of new-born agents, $v_t^h(a,\varepsilon^h)$ is the value function of a high skill agent that depends on the asset holdings and on the realization of the labor endowment shock ε^h.[5] $v_t^\ell(a,\varepsilon^\ell)$ is, similarly, the value function of a low-skill agent. The value of becoming a high-skill is reduced by a fixed cost, $\theta(a)$, which decreases with the level of capital. The expectations are formed using the stationary Markov distributions which are type-specific.

Once the decision regarding the type is taken, the agent i solves the following problem, with $j = \{\ell, h\}$:

$$v_t^j(a_{i,t},\varepsilon_{i,t}^j) = \max_{c_t, a_{t+1}}\left\{u(c_{i,t}) + \beta(1-d)\sum_{\varepsilon_{t+1}^j}\pi\left(\varepsilon_{t+1}^j \mid \varepsilon_{i,t}^j\right)v_{t+1}^j\left(a_{i,t+1},\varepsilon_{i,t+1}^j\right)\right\}, \tag{1.2}$$

$$\text{subject to}\quad c_{i,t} + a_{i,t+1} = (1 + r_t - \delta)a_{i,t} + w_t^j\cdot\varepsilon_{i,t}^j,\quad\text{and}\quad a_t > 0.$$

Where w_t^j is the type-specific wage rate and $\varepsilon_{i,t}^j$ is the idiosyncratic shock, which follows a type-specific Markov process. r_t is the interest rate and δ is capital depreciation.

Production Side:

As mentioned, the production side borrows from Acemoglu and Restrepo, 2018. In that paper, they build a representative agent model combined with

[5] I refer to the shock as "labor endowment" as in Aiyagari, 1994. In the literatiure is maybe more common to use "productivity shocks", however, in this model the shock does not change the productivity of the agents which is a very precise thing in the production side (see below). The productivity of the agent determines her wage rate, while, the shock, together with the wage rate determines the total labor income.'

task-based production with capital and labor. Then, in an extension (see page 1519), they propose a way to model heterogeneous skills in their task-based production and characterize balance growth path wage inequality depending on the difference between productivities between high and low-skill labor. They do this exercise with fixed shares of labor skill types. In this paper, I use the framework developed in that extension.

There is a unique final good produced with a continuum of tasks:

$$lnY = \int_{N-1}^{N} ln[y(x)]dx,$$

where Y is the output of the final good and $y(x)$ is the quantity of task x produced. The final good is produced with a unit measure of tasks that ranges from $N-1$ to N. An increase in N, which corresponds to the introduction of new tasks, does not alter the total measure of tasks in the economy. Each task is produced with a linear production function as in Equation (1.3). Where, for instance, $m(x)$ is the amount of capital (machines) used in the production of task x and $\gamma_m(x)$ is the productivity of capital in the production of task x. $\gamma_m(x)$ is, therefore, the productivity schedule of capital: a function that for every task gives the productivity of capital in that task. Similarly for the other factors of production.

$$y(x) = \gamma_m(x)m(x) + \gamma_\ell(x)l(x) + \gamma_h(x)h(x). \tag{1.3}$$

The relationship between the productivity schedules of capital and the two productivity schedules of labor determines how the production of tasks is split between capital and labor. I assume the following:

Assumption 1

$$\frac{d}{dx}\left(\frac{\gamma_\ell(x)}{\gamma_m(x)}\right) > 0 \quad \text{and} \quad \frac{d}{dx}\left(\frac{\gamma_h(x)}{\gamma_m(x)}\right) > 0. \tag{A1}$$

This implies that labor has a comparative advantage in higher indexed tasks. And, Assumption 2

$$\gamma_l(x) = \begin{cases} \gamma_h(x) & x \leq \bar{N} \\ \gamma_h(x) \cdot \Gamma & x > \bar{N} \end{cases} \tag{A2}$$

Where $\Gamma < 1$. High-skill labor has a comparative advantage in higher index task with respect to low-skills. $\bar{N}$ can be thought of as a division between old and new tasks, or complex and non-complex tasks.
The highest indexed task produced with capital, $\tilde{I}$, is given by solving the following equation,

$$\tilde{I} : \frac{r}{\gamma_m(\tilde{I})} = \frac{w_\ell}{\gamma_\ell(\tilde{I})}.$$

Hence, $\tilde{I}$ is the task in which the effective costs - price over productivity - of capital and labor are equal. The division between high and low-skills in the labor area follows a similar logic. However, given the discontinuity in the productivity of the low-skills, there is not one clear equation that pins down the separation threshold, as we have for the division capital-labor. Therefore, for simplicity, I restrict the attention to the case in which the following condition is verified:[6]

Assumption 3

$$\Gamma < \frac{w_\ell}{w_h} < 1. \tag{A3}$$

This in turn implies the following:

$$\frac{w_\ell}{\gamma_\ell(x)} < \frac{w_h}{\gamma_h(x)} \quad \text{if} \quad x < \bar{N},$$
$$\frac{w_\ell}{\gamma_\ell(x)} > \frac{w_h}{\gamma_h(x)} \quad \text{if} \quad x > \bar{N}.$$

The left hand side of both equations is the effective cost of producing tasks with low-skill labor while, the right hand side is the same variable for high-skills. These equations tell us that when assumptions A2 and A3 are satisfied, only high-skills are employed in *new* tasks and only low-skills are employed in *old* tasks. The separation threshold between the two types of labor is equal to $\bar{N}$. Assumptions A1, A2 and A3 imply that the unit measure of tasks is divided into three areas: tasks performed by capital, tasks performed by low-skill labor, and tasks performed by high skill labor (see Figure 1.1).

Automation is modeled in the following way. As said, $\tilde{I}$ is the highest indexed task that is optimal to automate given productivity schedules and

[6] This assumption is made on endogenous objects and must be verified ex-post in equilibrium.

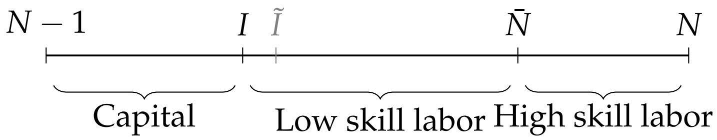

FIGURE 1.1: Allocation of factors of production in the unit measure of tasks.

factor prices. I now define I as the highest indexed task that is *feasible* to automate. This means that for $x > I$ simply does not exist the technology that allows producers to use machines to perform these tasks. In general, then, the highest indexed task automated in equilibrium, I^*, is equal to

$$I^* = \min\{I, \tilde{I}\}.$$

For some combinations of the parameters in the model, the profit maximization problem of the firm is constrained in the equilibrium, that is $I^* = I$. In these cases, automation is a *relaxation* of this constraint, an increase in I. For the rest of the paper, I focus on this case because is the only one which allows me to study the implication of an invention in automation technology. Indeed, when some automation technologies are not adopted ($\tilde{I} < I$), an increase in I has absolutely no effects on the equilibrium in this model.
The total output, Y, can be rewritten as a Cobb Douglas in the three factors of production, in which, crucially, factors' shares are endogenous and depend on technology.[7]

$$Y = G\left(\frac{K}{I-N+1}\right)^{I-N+1}\left(\frac{L}{\bar{N}-I}\right)^{\bar{N}-I}\left(\frac{H}{N-\bar{N}}\right)^{N-\bar{N}}. \tag{1.4}$$

The expressions of factors' prices take the usual form,

$$r = Y \cdot \frac{I-N+1}{K}, \tag{1.5}$$

$$w_\ell = Y \cdot \frac{\bar{N}-I}{L}, \tag{1.6}$$

$$w_h = Y \cdot \frac{N-\bar{N}}{H}. \tag{1.7}$$

[7] With

$$G = \exp\left(\int_{N-1}^{I} \ln(\gamma_m)\,dx + \int_{I}^{\bar{N}} \ln(\gamma_\ell(x))\,dx + \int_{\bar{N}}^{N} \ln(\gamma_h(x))\,dx\right).$$

The price of each factor is proportional to total output and to the share of the factor in aggregate production, and inversely proportional to the supply of the factor.

Before turning to the definition of equilibrium, it is useful to describe the transition of the distribution between a generic period t and $t+1$. In every period t, each agent is characterized by three variables, the level of assets she owns, $a_{i,t}$, the Markov state $\varepsilon^j_{i,t}$ and, her education level, e_i. λ_t is the distribution of agents over states at time t. At the end of the period, a random sample of size d - which corresponds to the probability of dying in t - is drawn from λ_t. Before the beginning of the next period, the deceased agents are replaced by their offspring who inherit their level of capital. First, they decide their level of education based on (1.1). Second, their Markov state realizes based on the education-specific stationary Markov distribution. The transition of the agents who do not die in period t into a new position in state space in $t+1$ depends on the solution of the value function (1.2) - that depends on their level of asset holdings, Markov state, and education type - and on the realization of the idiosyncratic shock in $t+1$.

Equilibrium:
Given a sequence of technological parameters $\{I_t\}_{t=0}^{\infty}$ and $\{N_t\}_{t=0}^{\infty}$, a recursive competitive equilibrium are sequences of value functions $\left\{v^h_t\right\}_{t=0}^{\infty}$ and $\left\{v^\ell_t\right\}_{t=0}^{\infty}$, policy functions $\left\{c^h_t, a^h_{t+1}\right\}_{t=0}^{\infty}$ and $\left\{c^\ell_t, a^\ell_{t+1}\right\}_{t=0}^{\infty}$, firm's choices $\{L_t, H_t, K_t\}_{t=0}^{\infty}$, prices $\left\{w^\ell_t, w^h_t, r_t\right\}_{t=0}^{\infty}$ and ditributions $\{\lambda_t\}_{t=0}^{\infty}$ such that, for all t:

- Given prices, the policy functions solve the agents' problems and the associated value functions are $\left\{v^h_t\right\}_{t=0}^{\infty}$ and $\left\{v^\ell_t\right\}_{t=0}^{\infty}$.

- Given prices and technology, firms choose optimally labor inputs and capital.

- The labor markets clear:

$$H_t = \left[\left(\Pi^{*,h}\right)^T \cdot \boldsymbol{\varepsilon}^h\right] S^h_t$$

$$L_t = \left[\left(\Pi^{*,\ell}\right)^T \cdot \boldsymbol{\varepsilon}^\ell\right] S^\ell_t$$

  Where $\Pi^{*,j}$ is the stationary distribution associated with the Markov process of type j; ε^j is a vector containing the values of the shock corresponding with the stationary distribution and S^j_t is the number of agents that belong to type j.

- The asset market clears:

$$K_t = \int_{A\times E} a_{t+1}(a_t, \varepsilon_t) d\lambda_t.$$

1.3 Quantitative Results

I now turn to the quantitative analysis of the model. First, I explain how I calibrate the model parameters. Then, with the calibrated model, I discuss the mechanism at play in the model. To do so, I report, separately, the transitional dynamics between steady-states for two different shocks: an increase in automation and an introduction of new tasks in which labor has a comparative advantage. For the sake of clarity, I assume that these shock are instantaneous, that is, the final steady-state value of the shock is reached immediately. In this way, it is easier to understand the reaction of the model economy with respect to a case in which the shock happens gradually. This strong assumption is relaxed in the main result of the paper, in which I compute the transitional dynamics with shocks estimated from the data. Finally, with a decomposition exercise, I quantitatively evaluate the contribution of various components of the model in determining the increase in inequality.

1.3.1 Bringing the model to the data

The composition adjusted college premium is reported in Figure 1.2. The data is taken from the March CPS database; I restrict the sample to include only full-time full-year workers with age between 16 and 64. This measure of the college premium, taken from Acemoglu and Autor, 2011, ensures that this statistic is not "mechanically affected by shift in experience, gender composition, or average level of completed schooling within the broader categories of college and high-school graduates".
I assume that the economy is in a steady state from year 1978 to 1981 - red dashed horizontal line in the graph - because in this period the college premium displays more stability relative to the whole period.

In Table 1.2 I report the calibrated parameters and the relative targets or sources used in the calibration. The table is divided into two parts: preferences and technology. The result of the calibration of the labor income risk

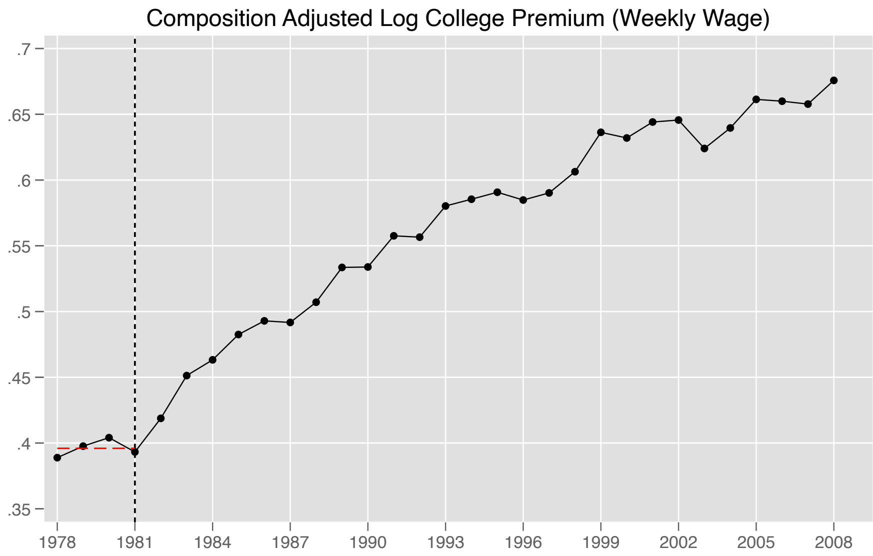

FIGURE 1.2: Composition-adjusted log college premium from 1978 to 2008 in the United States. Data from March CPS, full-time, full-year workers. The steady state value - red dashed line in the graph - is equal to 0.39. I use the estimation technique of Acemoglu and Autor, 2011.

parameters is excluded from the Table but is also discussed in this section. I now explain the reasoning behind the calibration strategy for each parameter.

Regarding the parameters that enter the preferences of the agents, I set the dying probability equal to 3% to imply an average working life of 33 years. To estimate the cost of education, I use as a target the average share of workers with a college degree in the US between 1963 and 1981, which is equal to 14%. The remaining parameters relative to the preferences of the agents have standard values taken from the literature.

All the parameters relative to the labor income risk that the agents face are calibrated using the estimates from Guvenen, 2009. Using data from the Panel Study of Income Dynamics (PSID) covering 1968 to 1993, he estimates an AR(1) income process separately for college and non-college graduates.[8] The values he estimates for the persistence and the variance of the innovation are reported in table 1.1.

I compute the associated Markov process using the Tauchen's method.

[8]Using Guvenen words, his sample consist of "*[...] male head of households between the ages of 20 and 64. I include an individual into the sample if he satisfies the following conditions for twenty (not necessarily consecutive) years: the individual has (1) reported positive labor earnings and hours; (2) worked between 520 and 5110 hours in a given year; (3) had an average hourly earnings between a preset minimum and a maximum wage rate (to filter out extreme observations). I also exclude individuals who belong to the poverty (SEO) subsample in 1968*".

Parameters	Values
ρ_ℓ	.829
σ^2_ℓ	.022
ρ_h	.805
σ^2_h	.025

TABLE 1.1: Values from Guvenen, 2009.

When doing this, I have to set the number of Markov states, S, and the maximum number of standard deviation from the mean, i.e. the dispersion of the Markov's state space. I set $S = 9$ and $max(SD) = 1$. From the discretization, I obtain the conditional probabilities of the Markov matrix, Π^i, and the vector of Markov states, ε^i. Given that Guvenen uses log labor earnings to estimate the labor income risk parameters, I have to normalize the values of the Markov process to have $\mathbb{E}(\exp(\varepsilon_i^j)) = 1$. To do this, I symmetrically shift the values found with the Tauchen method.

I now turn to the discussion of the parameters of the production side of the economy.

I normalize the highest-indexed task in the economy $N_0 = 1$ (the sub-index "0" indicates the initial steady-state). To compute the highest indexed task automated in equilibrium I use the following relationship that holds in the model:[9]

$$I_t = N_t - (\text{LABOR SHARE})_t.$$

The series of the Labor Share (LS) is a crucial object for the result of this paper, as this is used to impute the level of automation in the initial steady-state and, as will be explained in the following section, to estimate the sequences of the technology parameters.

The remaining four parameters ($\tilde{\gamma}$, q_y, m, $\bar{N}$) in Table 1.2 determine the shape of the productivity schedules of the factors of production. The functional

[9] From the definition of the labor share,

$$LS = \frac{w_h H + w_\ell L}{Y},$$

substitute the expressions for the wages, (1.6) and (1.7), to obtain,

$$LS = \frac{Y(N - \bar{N}) + Y(\bar{N} - I)}{Y} = N - I.$$

FIGURE 1.3: Labor share. Data from the Bureau of Economic Analysis. The average value of the labor share in the initial steady-state is 0.64.

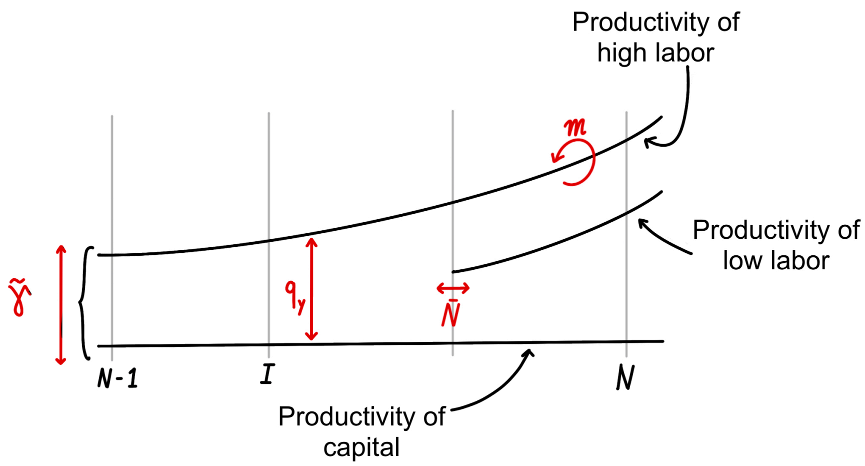

FIGURE 1.4: Productivity schedules of inputs of production. In red, the parameters to calibrate.

forms chosen for the productivity schedules are the following:

$$\gamma_h(x) = \tilde{\gamma} \cdot q_y \cdot e^{m(x - \frac{I+N}{2})} \tag{1.8}$$

$$\gamma_\ell(x) = \begin{cases} \gamma_h(x) & x \leq \bar{N} \\ \gamma_h(x) \cdot \Gamma & x > \bar{N} \end{cases} \tag{1.9}$$

$$\gamma_m(x) = \tilde{\gamma} \tag{1.10}$$

To have a sense of how the to-be-calibrated parameters affect the shapes of

	DESCRIPTION	VALUE	TARGET/SOURCE
PREFERENCES			
σ	Risk Aversion	2	Standard
β	Discount	0.95	Standard
δ	Depreciation	6%	Standard
d	Death probability	3%	33 years average working life
$\tilde{\theta}$	Education Cost	15.04	Share of workers with col. degree
TECHNOLOGY			
N	Highest-indexed task	1	Normalization
I	Highest-indexed automated task	0.35	Labor share $= 0.66$
$\tilde{\gamma}$	Productivity	0.12	$K/Y = 3$
q_y	Productivity of labor 1	0.7	Cost saving = 30%
m	Productivity of labor 2	1.66	$\hat{z} = 1.67$
$\bar{N}$	Highest-indexed task non-college	0.84	Log college premium $= 0.43$

TABLE 1.2: Calibrated parameters of the model.

the productivity schedules, take a look at Figure 1.4. $\tilde{\gamma}$ determines the aggregate productivity as an increase in this parameter shifts up all productivity schedules. q_y determines the difference between the productivity of capital and that of labor. $\bar{N}$ controls the difference between the productivity schedule of unskilled and skilled labor while m regulates the slope of the productivity schedule of labor.

As will be more precisely explained in the following section, the effect of task automation on the economy crucially depends on the trade-off between the displacement and the productivity effect. The displacement effect depends on how tasks automation changes the relative demand for factors, as an increase in I decreases the size of the set of tasks performed by low-skills and increases the size of the set of tasks performed by capital. However, automation also increases productivity and this tends to increase all factor prices. I specify the productivity schedule in (1.8) so that the parameter m determines precisely this trade-off. As m increases, for a given productivity of capital and a given displacement effect, the cost-saving (and therefore the productivity effect) implied by automation is greater. The chosen specification for the productivity schedule in (1.8) implies that, in the initial steady-state, a change in the parameter m within a range of values, does not change the equilibrium of the model economy. This is because it does not change the aggregate productivity G and does not change the relative demand for factors.[10] In this way, m is directly linked with the previously mentioned trade-off. m reflects also the difference between the average productivity of workers with a college degree and the average productivity of workers without a college degree. Indeed, as m increases, the average productivity of college workers increases relative to non-college workers. This is perfectly consistent with the relationship between m and the trade-off. As the productivity of the workers who will be automated increases, the cost-saving coming from automation decreases, and the impact of automation on the economy changes. To calibrate this parameter, I use, therefore, the following statistics:

$$\hat{z} = \frac{\text{Average workplace productivity of workers with a college degree}}{\text{Average workplace productivity of workers without a college degree}}$$

I take the estimate for $\hat{z}$ from Hellerstein, Neumark, and Troske, 1999: $\hat{z} = 1.67$. In this paper, the authors estimate precisely the difference in productivity between workers with and without college education. To build the counterpart of this statistic in the model, I use the implication of assumption A2 and A3 about the labor productivity schedule. In the initial steady-state, low-skill workers perform tasks between I and $\bar{N}$ and skilled workers between $\bar{N}$ and N. The average productivity of a low-skill worker is

$$\bar{\ell} = \frac{\int_I^{\bar{N}} \gamma_\ell(x) \cdot \frac{L}{\bar{N}-I} dx}{L}.$$

While for high-skill workers,

$$\bar{h} = \frac{\int_{\bar{N}}^{\bar{N}} \gamma_h(x) \cdot \frac{H}{N-\bar{N}} dx}{H}.$$

Finally, the moment condition I sue to calibrate m is,

$$\frac{\bar{h}(m)}{\bar{\ell}(m)} = \hat{z}.$$

[10]Wages in this model change because of two reasons (i) the aggregate productivity G changes (ii) the relative demand for factors change. The aggregate productivity does not change with m because, thanks to the specific chosen functional form, as, for instance, m increases, the productivity of skilled workers increases but the productivity of low-skills decreases in a way that perfectly offsets the effect on aggregate productivity. Moreover, the change in productivity does not change the relative demand of labor because, on one side, there is the technological constraint (I) and, on the other side - the threshold that separates the two types of labor - there is the discontinuity of the productivity schedule of the low-skill workers.

Which, after plugging the expressions for $\bar{\ell}$ and $\bar{h}$ becomes,

$$\frac{\exp(mN) - \exp(m\bar{N})}{\exp(m\bar{N}) - \exp(mI)} \cdot \frac{\bar{N} - I}{N - \bar{N}} = \hat{z}. \tag{1.11}$$

To calibrate q_y I use the estimate from Acemoglu and Restrepo, 2017 of the cost-saving associated with the adoption of automation technology. To pin down $\tilde{\gamma}$ I use the capital-output ratio. Finally, for $\bar{N}$, I use the adjusted log college premium, $\widehat{CP}$ (average value over the period 1963-1981, see Figure 1.2). Given that $\widehat{CP}$ is the difference between the average log wages for the two education groups, the moment condition is not simply $log\,(w_h/w_\ell) = \widehat{CP}$. To explain the derivation of this moment condition, I use the example of a three state Markov process. The average log wage for low-skills is

$$\begin{gathered}\pi_1^{*,\ell}\log\left(w_\ell\varepsilon_1^\ell\right) + \pi_2^{*,\ell}\log\left(w_\ell\varepsilon_2^\ell\right) + \pi_3^{*,\ell}\log\left(w_\ell\varepsilon_3^\ell\right) = \\ \log\left(w_\ell\right)\underbrace{\left(\pi_1^* + \pi_2^* + \pi_3^*\right)}_{1} + \left(\Pi^{*,\ell}\right)^T\log\left(\varepsilon^\ell\right) = \\ \log\left(w_\ell\right) + \left(\Pi^{*,\ell}\right)^T\log\left(\varepsilon^\ell\right).\end{gathered} \tag{1.12}$$

Where $\Pi^{*,j}$ is the stationary distribution associated with the type-specific Markov process. Hence, the moment condition is

$$\begin{aligned}\overline{\log\left(w_h\right)} - \overline{\log\left(w_\ell\right)} = \log\left(w_h\right) - \log\left(w_\ell\right) + \\ + \left(\Pi^{*,h}\right)^T\log\left(\varepsilon^h\right) - \left(\Pi^{*,\ell}\right)^T\log\left(\varepsilon^\ell\right) = \widehat{CP}.\end{aligned} \tag{1.13}$$

Which, given the model expression of the wage ratio,

$$\frac{w_h}{w_\ell} = \frac{N - \bar{N}}{\bar{N} - I} \cdot \frac{L}{H}, \tag{1.14}$$

becomes,

$$\log\left(\frac{N - \bar{N}}{\bar{N} - I} \cdot \frac{L}{H}\right) + \left(\Pi^{*,h}\right)^T\log\left(\varepsilon^h\right) - \left(\Pi^{*,\ell}\right)^T\log\left(\varepsilon^\ell\right) = \widehat{CP}. \tag{1.15}$$

In Tables 1.3 I report the model generated moments used in the calibration and their data counterparts. In Table 1.4 I report the Gini's coefficients of the wealth and consumption distribution of the simulated economy. These moment were not targeted directly. The model generates 57% of the wealth inequality observed in the data and 62% of the consumption inequality.

Expressions		Data/Targets	Model
$log\,(w_h/w_\ell)$	Log coll. premium	0.39	0.39
$\hat{z}$	Prod. ratio	1.67	1.67
K/Y	Capital/output	3	2.58
$\frac{w_\ell}{\gamma_\ell(I)}/\frac{r}{\gamma_m}$	Cost saving autom.	30%	30%
S_h	College share	18%	18%

TABLE 1.3: Calibration results, targeted moment.

Gini coefficients	Data	Model
Consumption	0.24	0.15
Wealth	0.77	0.44

TABLE 1.4: Untargeted moments. Source: Kuhn et al 2018 and Krueger and Perry 2006.

1.3.2 Mechanisms' Discussion

To analyze the effect of task automation and new task introduction, I now report, separately, one transition for each shock. First, look at Figure 1.5. In these graphs I show the transitional dynamics after a permanent and instantaneous increase in the tasks performed with machines (a 5% increase of I). To understand the reaction of the interest rate, capital and output, it is convenient to recall equation (1.5),

$$r = Y \cdot \frac{\uparrow I - N + 1}{K}$$

In the first period after the shock, the increase in I implies an instantaneous increase in the interest rate. Indeed, the reaction of the aggregate capital stock is sluggish and the supply of capital takes time and does not compensate immediately the increase in demand. As time goes by, agents start to accumulate more capital and the interest rate decreases until the final steady-state value. As more capital is accumulated, the output increases.

In the short run, the effect of automation on the wage of educated workers is unambiguously positive, as automation increases productivity and does not decrease the demand for educated labor. Instead, in the short run, the effect on the wage of workers without college education depends on the trade-off between the increase in productivity and the decrease in the number of tasks in which they are demanded by the firms, or, in other words, the fact that they are reallocated in a different set of tasks. This trade-off can be analyzed

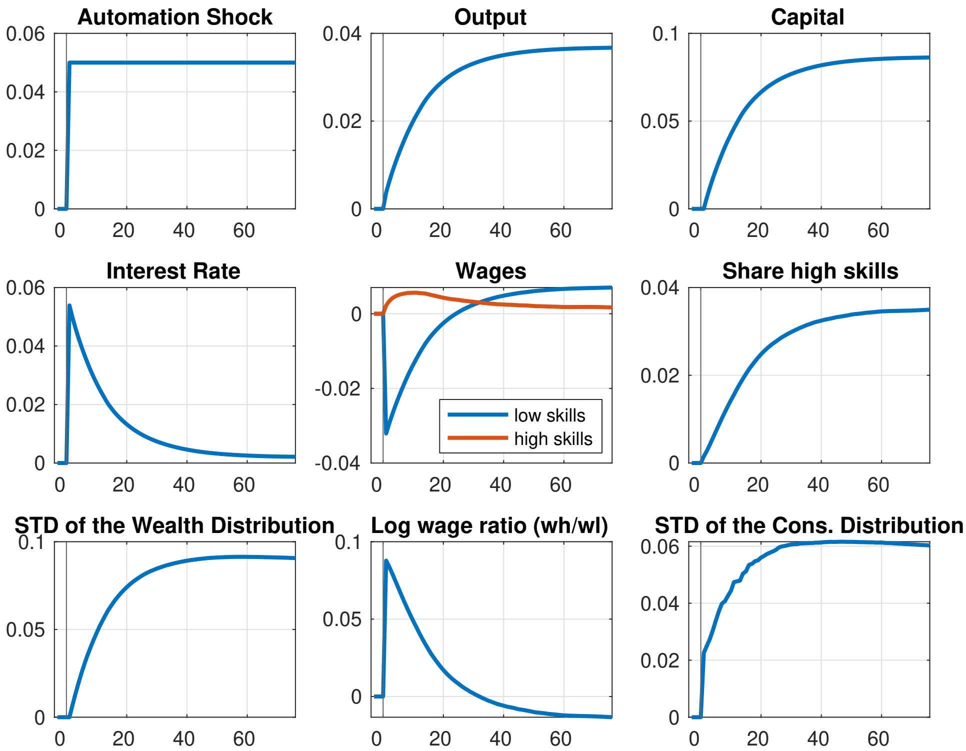

FIGURE 1.5: Transitional dynamics between the initial, calibrated steady-state and a final steady state in which the size of the set of tasks performed by capital has increased by 5%. All reported variables are normalized to zero in the initial steady-state.

by taking the following derivative:

$$\frac{d\ln w_\ell}{dI} = \underbrace{\frac{d\ln(Y/L)}{dI}}_{\text{Productivity Effect}} + \underbrace{\frac{d\ln(\bar{N}-I)}{dI}}_{\text{Reallocation Effect}} .$$

The productivity effect can be expressed in terms of productivities and prices,

$$\frac{d\ln w_\ell}{dI} = \underbrace{\ln\left(\frac{w_\ell}{\gamma_L(I)}\right) - \ln\left(\frac{r}{\gamma_m(I)}\right)}_{\text{Productivity Effect}} - \underbrace{\frac{1}{\bar{N}-I}}_{\text{Reallocation Effect}} . \tag{1.16}$$

Thanks to this manipulation, we can see that the productivity effect is greater the greater is the difference between the cost of producing task I with low-skill labor and with capital. In other words, the greater is the cost saved thanks to the automation adoption, the greater is the increase in productivity. Thus, whether the low-skill wage decreases in the short-run depends on

which of the two effects is bigger, which in turn depends on the comparative advantage structure and on the magnitude of the shock. With the chosen calibration for this model, the reallocation effect is stronger than the productivity effect in the short run. In the long-run, the accumulation of capital and the increase in the share of agents with a college education affect the transition of wages. The increase in capital tends to increase output and therefore both wages, while the increase in the number of educated workers decreases the wage of high-skill labor and increases the wage of the low-skills. To understand the difference between the short and the long-run, it is important to notice that while the reallocation effect is instantaneous, the implications of the productivity effect change over time as more and more capital is accumulated. For this reason, the reallocation effect can be greater than the productivity effect in the short-run, but the opposite can be true in the long-run. Hence, for a fixed reallocation of factor, the greater the productivity effect, the greater is the difference between the short- and the long-run effects.
To analyze the transition of the college premium and the share of educated workers, it is useful to report the expression of the wage ratio,

$$\frac{w_h}{w_\ell} \propto \frac{N - \bar{N}}{\bar{N} - \uparrow I} \cdot \frac{(1 - S_h)}{S_h},$$

and the problem of a new-born worker,

$$v_t^n(k) = \max \left\{ \uparrow \mathbb{E}_\varepsilon \left\{ v_t^h \left(k, \varepsilon^h \right) \right\} - \theta(k), \quad \mathbb{E}_\varepsilon \left\{ v_t^\ell \left(k, \varepsilon^\ell \right) \right\} \right\}.$$

Right after the shock, the immediate increase in the college premium implies an increase in the expected lifetime utility of high-skills relative to low-skills. For this reason, more agents decide to get education (increase in S_h) thus implying a decline in the college premium. However, there is another force that tends to increase the share of high-skill agents: as aggregate capital and per capita capital increase, also the average new-born worker becomes richer. As the cost of education is constant in the model, *more* agents can afford to get education. This last point explains why, in the final steady-state, the share of high-skills is higher than its value in the initial steady-state despite the college premium being lower. The increase in the interest rate increases wealth inequality, as the agents who own more capital benefit more from this increase. Also, the sudden jump in the college premium, allows college-educated workers to accumulate more capital. This boost in wealth

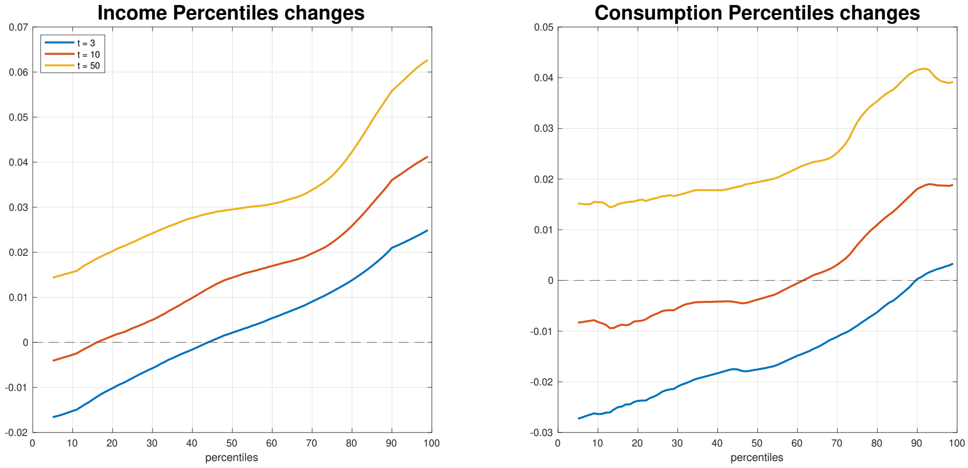

FIGURE 1.6: Percent variation of percentiles with respect to the initial steady-state value. Each line represents the variation a given number of years after the shock hits the economy. Left panel, total income distribution. Right panel, consumption distribution.

inequality, combined with the increase in wage inequality implies a permanent increase in the spread of the consumption distribution, measured with the standard deviation.

In Figure 1.6 I further focus on the effect of automation on inequality. To show how the total income and consumption distribution react to the sudden substitution between low-skill labor and capital in production, I report, for each distribution, the relative change with respect to the initial steady-state value of each percentile. In these graphs, each line represents the percentiles changes in a *given period* after the shock. The blue line depicts the change at $t = 3$, which is almost immediately after the shock. To understand what happens, recall that the wage of the uneducated workers decreases immediately but the interest rate increases. As a consequence, about half of the population in the model economy experience a decrease in total income when tasks are automated. This, despite the fact that the fraction of agents without a college degree is 82% in the initial steady-state (see Table 1.3). The reason is that uneducated workers who had a lucky series of shocks and managed to accumulate a relative big wealth, do not see their total income decrease, as the increase in the capital income *compensates* the decline in their return from the labor market. This highlights the importance of departing from the representative household model when studying the effect of technology on total income and consumption. In that model, as automation increases output, even if the labor income declines, the household is compensated with the increase in capital income. As a consequence, consumption and welfare necessarily increase. This is not true anymore with heterogeneous agents: only a small fraction of the agents who see their labor income drop benefit from greater capital income. The implication for consumption distribution can be seen in the right panel of the same figure. Right after the shock (blue line) percentiles up to the 85th decrease with respect to initial steady-state value. The decrease in consumption is greater than the one in the income distribution because agents are taking advantage of the high interest rate therefore postponing their consumption. As time goes by both distribution "shift to the right" and approximately after 50 years every percentile of both distribution is at a higher value.

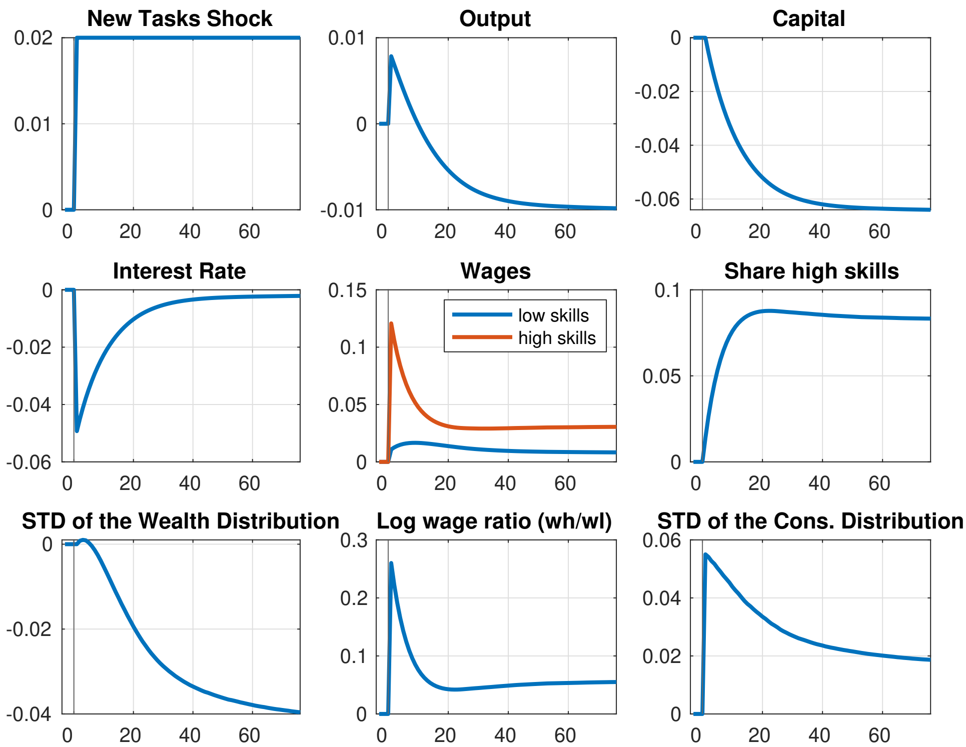

FIGURE 1.7: Transitional dynamics between the initial, calibrated steady-state and a final steady state in which the highest-indexed task in the economy, N, increases by 2%. All reported variables are normalized to zero in the initial steady-state.

In Figure 1.7 I show the transition after an introduction of tasks in which labor has a comparative advantage with respect to capital. In the short run, the introduction of new tasks increases productivity, and, consequently output increases. However, the production of the final good becomes more labor-intensive and the relative demand for capital decreases. The effect on the absolute demand for capital depends on the interaction between the boost in productivity and the decrease in the relative demand for capital;

with the chosen calibration the demand for capital decreases, as can be observed in the transition of the interest rate. The decrease in the interest rate implies that the aggregate level of capital starts decreasing, in turn implying a decrease in the production of the final good. Both wages increase because of the increase in productivity; however, the wage of educated workers increases more, as they also benefit from the increase in the relative demand for skilled labor. By looking at the following equation,

$$\frac{w_h}{w_\ell} \propto \frac{\uparrow N - \bar{N}}{\bar{N} - I} \cdot \frac{(1 - S_h)}{S_h},$$

it is clear why the college premium increases in the short run. Along with the transition, as more agents choose to get education given the increased premium, the gap between the wage of high- and low-skill workers declines until its final steady-state value. The effect on wealth inequality depends, as before, on the interaction between the effect on the return of capital and wage inequality. The increase in wage inequality dominates in the short-run, implying an increase in wealth inequality which, however, decreases along with the transition because of the lower interest rate and the decreasing college premium. For similar reasons, the standard deviation of the consumption distribution increases when new tasks are introduced and reaches its maximum right after the shock. After that, it starts to decline.

1.3.3 Estimation of the Shock

In the two transitions I showed in the previous subsection, the shocks are instantaneous and their magnitudes are chosen ad hoc to have the clearest possible dynamics. In this section, instead, I explain how I estimate from the data the sequences of the two technology variables $\{I_t, N_t\}$. In the following section, I use these estimated sequences to compute the transition that I then compare with the data. For the estimation of I_t and N_t, I use the series of the labor share as reported by the BEA (see Figure 1.3) and the expression that links, in the model, these two variables with the labor share, $I_t = N_t - (\text{LABOR SHARE})_t$. Given the initial values for I_0 and N_0 I adopt a similar technique as in Acemoglu and Restrepo, 2019 which in turn relies on the theory developed in Acemoglu and Restrepo, 2018: in a model with endogenous technological change, in a given period, is either profitable to develop technologies which are labor-intensive or automation technologies

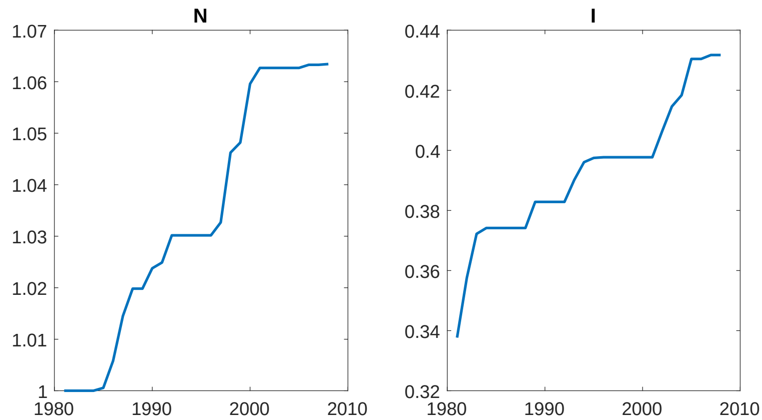

FIGURE 1.8: Estimated sequences of the technology parameters N - left panel - and I - right panel.

with the purpose of substituting labor in a given set of tasks. With this reasoning in mind, I assume that in a given period there are three possibilities: an increase in I, an increase in N, or no technological change. Following this logic, if the labor share increases I impute this increase to the introduction of new tasks, if it decreases, to the automation of tasks. This computation results in the sequences reported in Figure 1.8.

1.3.4 Transitional dynamics of the calibrated economy

In this section, I compute the transition of the model economy using the estimated sequences and compare the transition with real data in the period from 1981 to 2008. To simulate a balanced growth path, I extend the estimated sequences with linear trends until 50 years after the initial steady state. After this period, the technology parameters remain constant. As the agents discount the future and also have a probability of dying in every period, what happens in the first 30 years after the initial steady-state - which is the period under study - is not affected by what happens in a so remote future.

In Figure 1.9 I contrast the model generated series of consumption inequality with the data. For completeness, I report both the Gini's coefficient and the standard deviation of the distribution. The standard deviation implied by the model follows closely the increase in the spread of the distribution measured in the data until 1999. At that point, the inequality measured in the data increases relatively to the model. The Gini's coefficients are pretty close along the period under study: the model is able to generate the 14% increase in the Gini's coefficient. Consumption inequality depends on the college premium and on the fraction of workers with a college degree, for this reason, in Figure 1.10 I also contrast the evolution of these variables with the

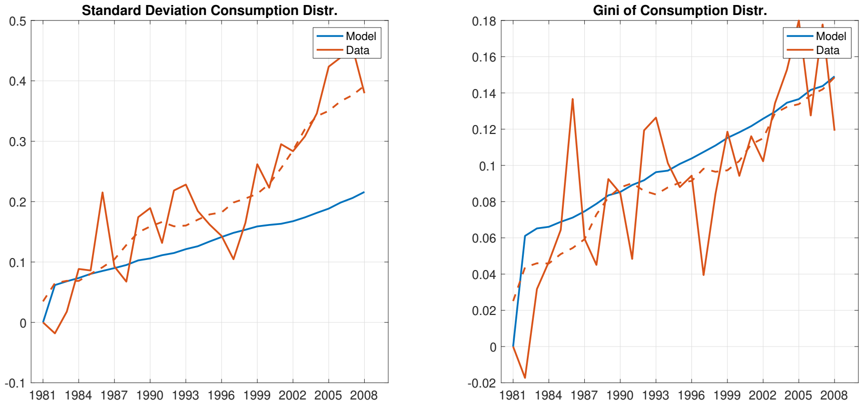

FIGURE 1.9: Evolution over time of the standard deviation and the Gini's coefficient of the consumption distribution. The model generated series are contrasted with the data counterparts. All values are normalized to zero in 1981. For illustrative purposes, I also report the 10-year moving average for the data series.

data. The model is able to explain around 35% of the increase in the college premium and around 63% of the increase in the share of educated workers.

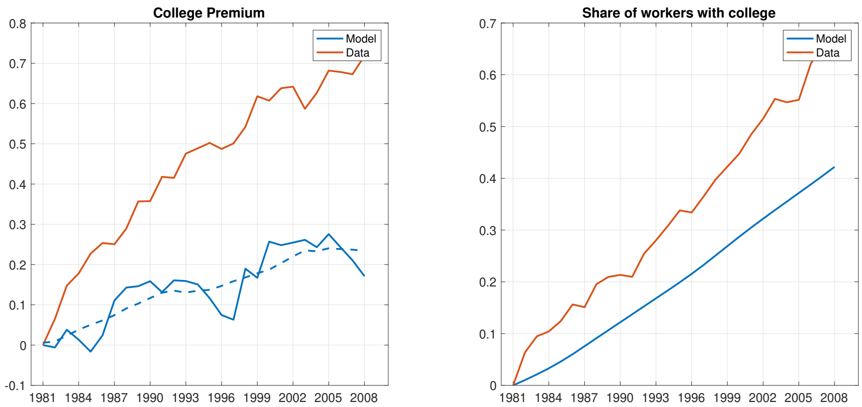

FIGURE 1.10: Evolution over time of the college premium and the share of workers with a college degree. The model generated series are contrasted with the data counterparts. All values are normalized to zero in 1981. For illustrative purposes, I also report the 10-year moving average for model generate college premium.

1.3.5 Effect Decomposition

In this section, I analyze the role played by task automation, the introduction of new tasks, the return of wealth, and endogenous education decision in the transition showed in the previous section. To understand the role of these components I compute the transition keeping the component fixed to

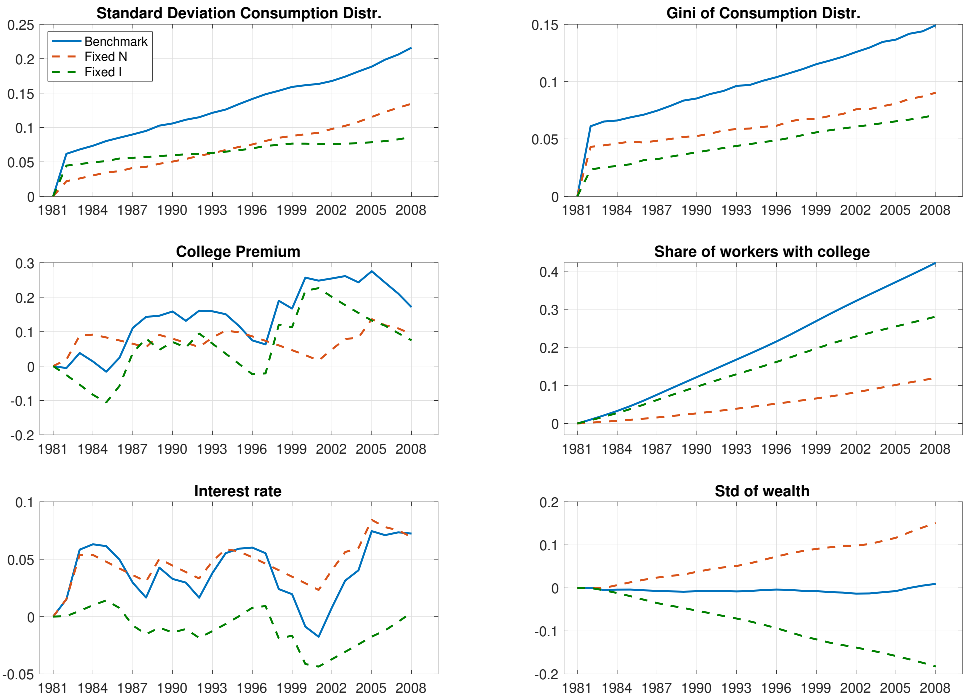

FIGURE 1.11: This figure compares the benchmark transition with two transitions in which I fix the automation of tasks and the introduction of new tasks.

the initial steady-state value. In Figure 1.11 I report the transition in which I fix the capital intensity to the initial steady-state value, the transition with no introduction of new tasks, and the benchmark transition for comparison. From this figure, we see how task automation contributes to the increase in inequality. The college premium increases *less* when no tasks are automated and, as consequence, the share of college workers is also smaller along with the transition. Task automation also contributes to the increase in the return of wealth. The lower return to wealth combined with the lower college premium implies that both measures of consumption inequality are lower in every year under study when no tasks are automated.

In the same figure, we see how also the new task introduction contributes to the increase in consumption inequality. First, the introduction of new tasks increases the college premium. Second, as the relative demand of capital decreases because production becomes more labor-intensive, tasks introduction decreases the value of the return to wealth. This has the effect of decreasing wealth inequality. However, the increase in the college premium dominates and, according to the model, the introduction of new tasks has contributed to the observed increase in consumption inequality between 1981 and 2008.

In Figure 1.12 I report the transition with a fixed return to wealth and fixed education shares. Similarly to the previous exercises, I fix the interest rate to

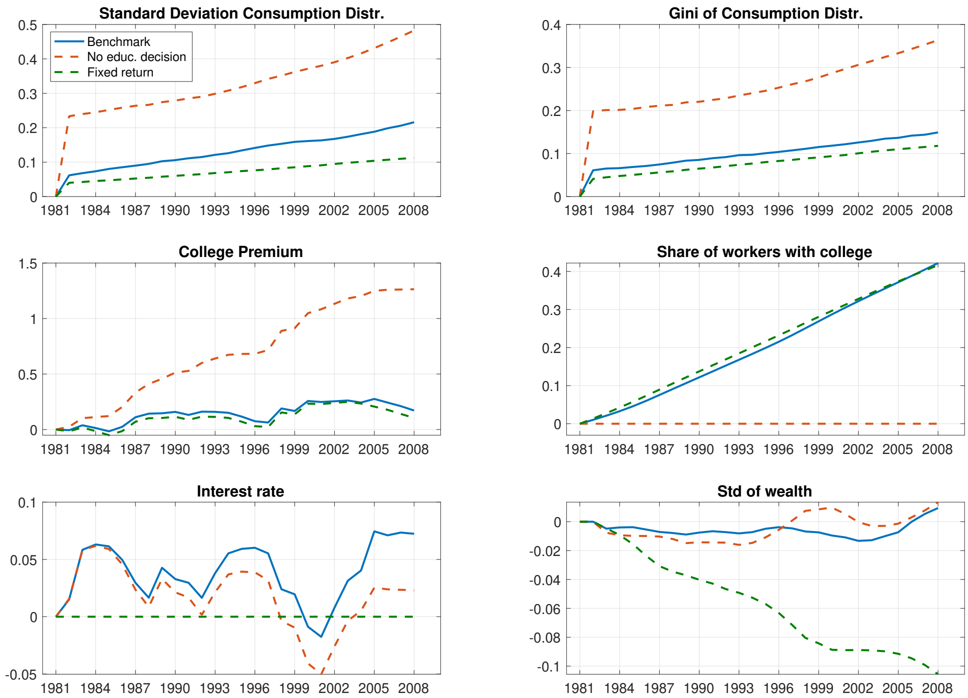

FIGURE 1.12: This figure compares the benchmark transition with two transitions in which I shut down the educational choice decision and the increase in the return to wealth.

the initial steady-state value. As the interest rate is an endogenous variable in the model, fixing it implies that, along with the transition and in the final steady-state the capital supply does not equal the capital demand. This exercise shows the importance of taking into account heterogeneous capital accumulation when studying the implication of technological change on inequality. Indeed, the increase in the interest rate contributes to the growth of consumption inequality by almost 4%.

In the same figure, I report the transition in which agents do not have the opportunity to choose their education. The way I do this in practice is to set to zero the probability of dying, d, in the household optimization problem. In this way, the shares of college and non-college-educated agents remain fixed to the initial steady-state level. When the labor force does not adjust the skill supply, the level of inequality is much higher. The college premium increases dramatically more with respect to the benchmark transition. As the college premium increases, both measures of consumption inequality increase *more* as well. The role of educational choice is therefore to buffer the increase in inequality implied by technological change.

1.4 Conclusion

I study the relationship between automation and consumption inequality by combining two theoretical frameworks. I use an incomplete market model à la Ayiagari with endogenous educational choice with a task-based model borrowed from Acemoglu and Restrepo, 2018. After calibrating the model to the US economy between 1978 and 1980 I first show what are the effects of a sudden adoption of automation technology and a sudden introduction of new tasks. I do that by computing the transitional dynamics from the initial steady-state. In particular, I show that automation decreases the labor income of uneducated workers and that the implied increase in the return to wealth counteracts that drop only for the uneducated rich. As the high-skill workers earn more and have, on average, higher wealth, the increase in the return to wealth widens the gap between the total income of high- and low-skills.

After estimating the series of automation and new tasks creation from the data, I compute the model implied transition and contrast this with the data. The model is able to replicate the increase in consumption inequality that took place in the US between 1981 and 2007. Finally, I decompose the effects of various components of the model along with the transition. I find that both educational choice and the return to wealth channel are quantitatively important in accounting for the increase in consumption inequality.

A natural use of the calibrated model developed in this paper is to use it for policy analysis. Regarding the possible effect of massive adoption of automation technology, a tax on robots has been proposed and evaluated by economists.[11] This is left for future research.

[11] For example, Guerreiro, Rebelo, and Teles, 2017.

Chapter 2

Automation and Sectoral Reallocation

With Dennis HUTSCHENREITER and Eugenia VELLA

Abstract

Empirical evidence in Dauth, Findeisen, Suedekum, and Woessner (2021) suggests that industrial robot adoption in Germany has led to a sectoral reallocation of employment from manufacturing to services, leaving total employment unaffected. We rationalize this evidence through the lens of a general equilibrium model with two sectors, matching frictions, and endogenous participation. Automation induces firms to create fewer vacancies and job seekers to search less in the automatable sector (manufacturing). The service sector experiences a positive spillover effect due to the sectoral complementarity in the production of the final good and the positive income effect for the household. Analysis across steady states shows that the reduction in manufacturing employment can be offset by the increase in service employment. The model can also replicate the magnitude of the decline in the ratio of manufacturing employment to service employment in Germany from 1994 to 2014.

We acknowledge financial support from the Spanish Ministry of Economy and Competitiveness, through the Seed Grant ("Job Automation, Domestic Migration and Occupational Mobility") of the Barcelona Graduate School of Economics Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2015-0563) for the use of robot data.

2.1 Introduction

As a result of improved capabilities and falling production costs, the global operational stock of industrial robots rose by about 65% within five years (2013-2018). The Covid-19 crisis is expected to accelerate further the speed of automation (see, e.g., Dolado, Felgueroso, and Jimeno, 2020 and Leduc and Liu, 2020a). In addition to the potentially significant implications for labor markets, recent evidence reveals that higher exposure to robot adoption has increased support for nationalist and radical-right parties in Western Europe (Anelli, Colantone, and Stanig, 2020).

Academic and policy debates have focused on whether robots cause job displacement or job creation in the economy. On the one hand, a negative displacement effect arises from the fact that robots can outperform workers in some tasks. For instance, Acemoglu and Restrepo, 2020 recently find that each robot installed in the US replaces six workers. On the other hand, a positive productivity effect occurs because machines can help fewer workers produce more output, which increases labor demand. In this vein, the seminal work by Graetz and Michaels, 2018 finds, using industry-level data from 17 countries, that cumulative changes in robot adoption from 1993 to 2007 boost labor productivity and raise wages.[1]

Notably, the adjustment in other parts of the economy and the potential sector spillover effects – for instance, when other sectors expand to absorb the labor freed from robot adoption – have received little attention so far. According to empirical evidence from Germany in Dauth, Findeisen, Suedekum, and Woessner, 2021, industrial robots have changed the composition but not the aggregate size of employment, with job gains in services offsetting the negative impact on manufacturing employment. Figure 2.1 shows the evolution of employment and employees' compensation (as a share of GDP) in the two sectors along with the stock of industrial robots in the country with the highest robot density in Europe (see Figure 2.2).

To rationalize the empirical evidence on the automation-driven sectoral reallocation of labor in Germany, we develop a general equilibrium model with two production sectors, a labor market participation choice, and matching frictions.[2] Automation increases the capital intensity of the technology in the manufacturing sector. Our modeling framework for automation (see

[1]There are two main strands in the literature regarding a tangible measure of automation: information-and-communication-technology capital (see, e.g., Eden and Gaggl, 2018) and robotics (see, e.g., Graetz and Michaels, 2018).

[2]For empirical work on the decline in manufacturing and the rise in services, see a novel dataset for 10 sectors, 23 countries, and 150 years compiled by Priftis and Shakhnov, 2020.

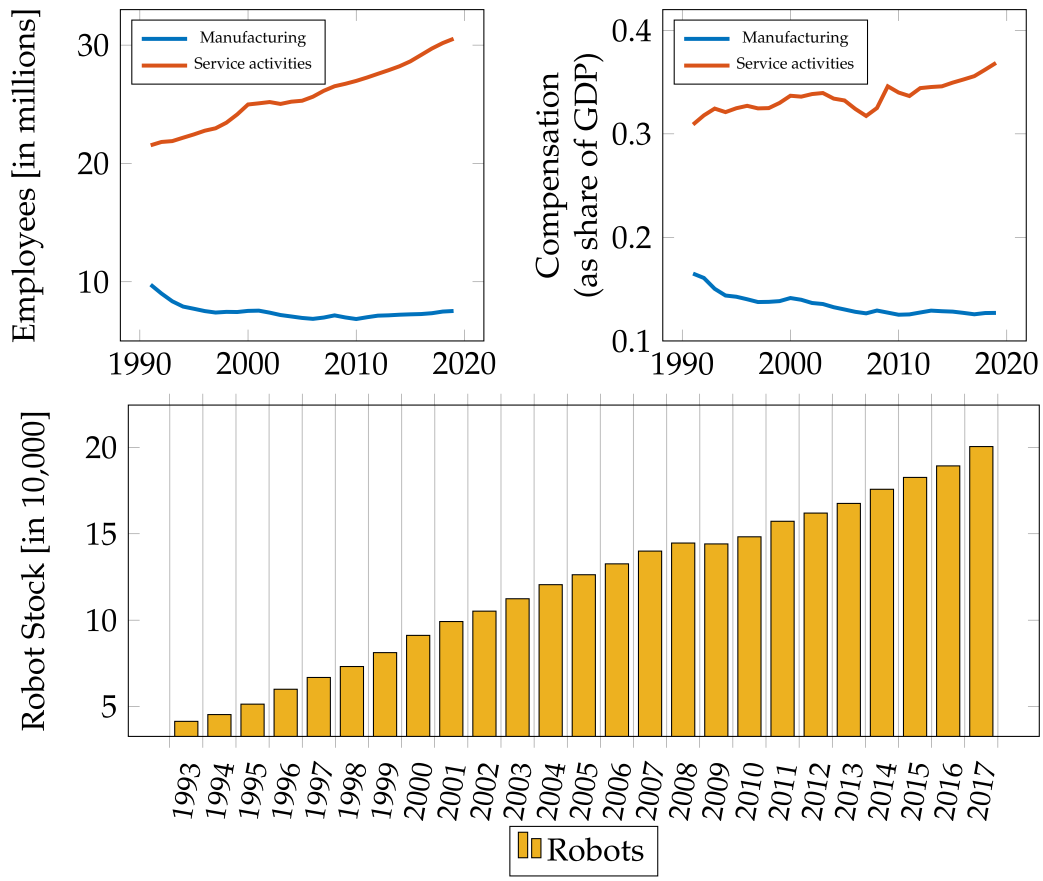

FIGURE 2.1: Industrial robots, employment and employees' compensation in Germany

Note: Numbers of employees and the levels of their compensation (as share of GDP) in the manufacturing and service sectors come from the Federal Statistical Office (Destatis). Data on the stock of industrial robots comes from the International Federation of Robotics (IFR).

Section 2.2) is consistent with the microfoundations derived by Acemoglu and Restrepo, 2018 and close in spirit to Bergholt, Furlanetto, and Faccioli, 2020.[3] The presence of unemployment in the model is crucial as we seek to explain how total employment can remain constant when labor reallocates between the two sectors. Without unemployment, that would be true by construction, while it is a result of our model. Furthermore, the inclusion of labor market frictions allows us to study the impact of automation on endogenous job creation. The presence of the extensive margin in our model is motivated by recent literature highlighting the negative effect of automation on participation (see, e.g., Lerch, 2020, Grigoli, Koczan, and Topalova, 2020, Jaimovich, Saporta-Eksten, Siu, and Yedid-Levi, 2020, and Lerch, 2020).

[3]Note that Bergholt, Furlanetto, and Faccioli, 2020 examine impulse responses from a New Keynesian model, while we focus on long-run effects through analysis across steady states.

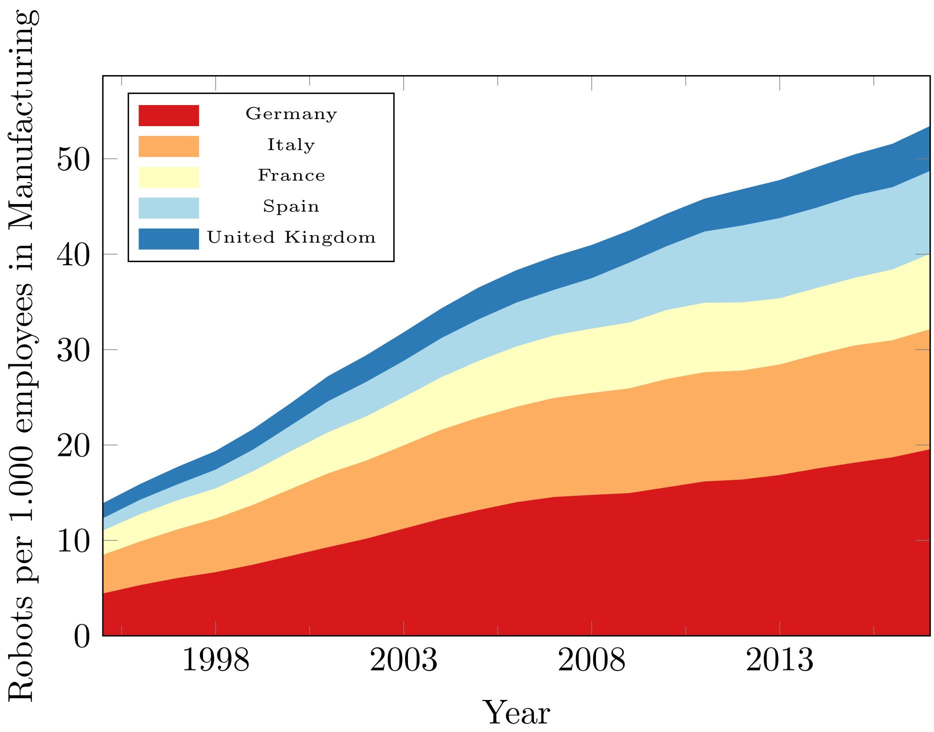

FIGURE 2.2: Industrial robot density in the manufacturing sector of European economies

Note: Data on the stock of industrial robots comes from the International Federation of Robotics (IFR). We define the manufacturing sector as the aggregate of Industries A-F in the German WZ08 industry classification.

Overall, the adjustment of sectoral labor markets in response to automation takes place in the model through three channels: (i) job creation, (ii) sector-specific search of unemployed job seekers, and (iii) participation. Since our representative household model is capable of rationalizing the empirical evidence mentioned above, we abstract from heterogeneous households for simplicity.

Our main findings can be summarized as follows. In the model, as in the empirics of Dauth, Findeisen, Suedekum, and Woessner, 2021, automation induces firms to create fewer vacancies and job seekers to search less in the robot-exposed sector (manufacturing). The model is able to replicate the empirical evolution of employment and employees' compensation in manufacturing and services (Figure 2.1). The service sector experiences a positive spillover effect and expands. Labor demand in services increases since the two sectoral goods are gross complements in the production of the final consumption good. This result is consistent with the model of Acemoglu and Restrepo, 2020, where higher robot adoption increases demand for complementary inputs. Additionally, as income rises, consumption demand increases (positive income effect), also contributing to the spillover effect. Calibrating the model for Germany, we show through analysis across steady states that the reduction in manufacturing employment can be offset by the increase in service employment, thus leaving aggregate employment mostly unaffected.

Our analysis highlights vacancy creation (labor demand) as the primary channel through which the two labor markets adjust to automation. The elasticities of substitution between capital and labor in manufacturing production and between automatable (manufacturing) and non-automatable (service) goods play an important role in the sectoral reallocation of labor, while the sectoral mobility of job seekers and the positive income effect also matter. Furthermore, the model generates a negative effect of automation on labor market participation in line with the literature, but, overall, results do not depend crucially on the extensive margin.

The model can replicate the magnitude of the decline in the ratio of manufacturing employment to service employment in Germany from 1994 to 2014. Specifically, we take from the German data the values of the capital share in manufacturing in these two years. Then, we compute the values of the degree of automation in our model that generate these two values in the corresponding steady states, keeping the rest of the calibration unchanged. We find that in the second steady state (for 2014) the model predicts a decline of 27% in the ratio of manufacturing employment to service employment, which is close to the one found in the data (32%).

Related Literature. Abstracting from labor market frictions, Bergholt, Furlanetto, and Faccioli, 2020 examine impulse responses to an automation shock, modeled as an exogenous increase in the weight of capital in the production function of a New Keynesian model. They find that, among four possible explanations, automation is the main driver of the long-run labor share. In macroeconomic models with labor frictions, the role of automation remains little explored. Leduc and Liu, 2020b provide the first quantitative general equilibrium evaluation of the interaction between automation and labor market fluctuations over the business cycle. Automation acts as an endogenous wage rigidity by posing a threat to workers in wage negotiations. Leduc and Liu, 2020a extend the previous Real Business Cycle model with nominal rigidities. They find that pandemic-induced uncertainty shocks to worker productivity stimulate automation, which helps mitigate the negative impact on aggregate demand. Models with automation, heterogeneous households, and matching frictions are developed by Cords and Prettner, 2019 and

Jaimovich, Saporta-Eksten, Siu, and Yedid-Levi, 2020 to study the impact on inequality.

Very few studies in the automation literature have considered a two-sector economy without accounting for labor market frictions. Focusing on inequality, Berg, Buffie, and Zanna, 2018 show that the inclusion of a non-automation sector amplifies the high-skill labor gains and low-skill labor losses from automation. A non-automatable sector is included in an overlapping generations setting by Sachs, Benzell, and LaGarda, 2019. The study shows how short-term increases in consumption enabled by robots may lead to long-term immiseration and how government intervention can take place. To the best of our knowledge, we are the first to build a two-sector general equilibrium model with search and matching frictions to analyze the long-run impact of automation on both sectoral and aggregate employment.

Structure. Section 2.2 lays out the model. Section 2.3 establishes the equilibrium relationship between relative labor demand and labor supply in the two-sector economy. Section 2.4 discusses the calibration strategy. Section 2.5 presents the results. Section 2.6 investigates the role of key parameters and features of the model. Section 2.7 concludes.

2.2 The Model

We construct a general equilibrium model featuring search and matching frictions, endogenous labor decisions, and two sectors (manufacturing and services). Figure 2.3 provides an overview of the model.

On the production side, there is a representative firm in each of the two sectors. Manufacturing output is produced with capital and labor as inputs, while output in services is produced with labor only. The outputs of the two sectors are costlessly aggregated into the final consumption good.

On the household side, there is a representative household consisting of employees, unemployed job seekers, and labor force nonparticipants. The household rents out its capital to the manufacturing firm, purchases the final consumption good, and receives dividends through owning the two firms.

2.2.1 Labor markets

Jobs are created through a matching function. For $j = M, S$ denoting the manufacturing and service sectors, let v_t^j be the number of vacancies and u_t^j

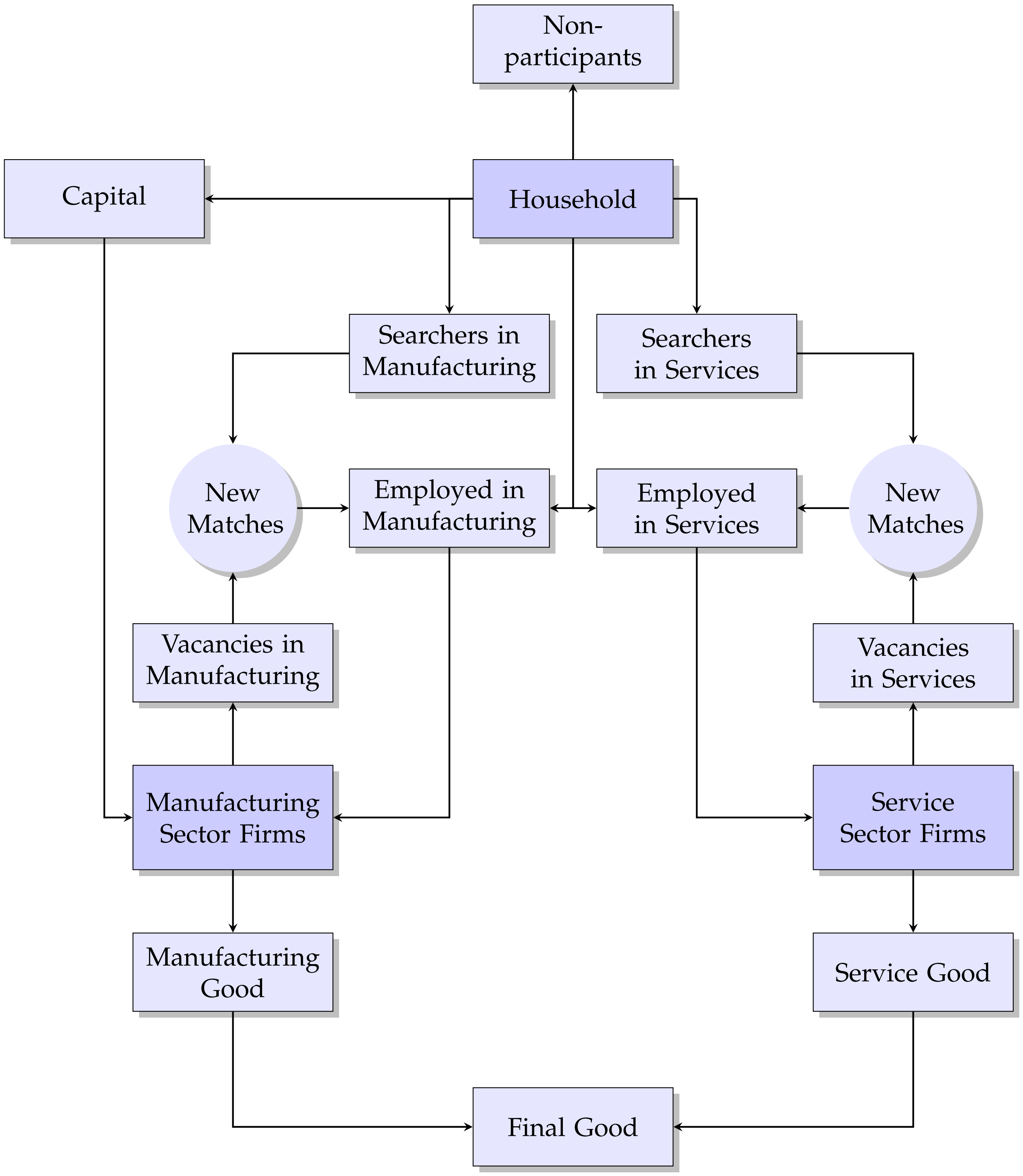

FIGURE 2.3: Model overview

the number of job seekers. We assume matching functions of the form,

$$m_t^j = \mu_1^j (v_t^j)^{\mu_2} (u_t^j)^{1-\mu_2}, \tag{2.1}$$

where the efficiency of the matching process is μ_1^j and μ_2^j denotes the elasticity of matches with respect to vacancies. For each sector, we define the hiring probability ψ_t^{hj} and the vacancy-filling probability ψ_t^{fj},

$$\psi_t^{hj} \equiv \frac{m_t^j}{u_t^j}, \qquad \psi_t^{fj} \equiv \frac{m_t^j}{v_t^j}.$$

Labor market tightness $\theta_t^j \equiv v_t^j / u_t^j$ determines the matching market prospects of firms and workers. The probability that a worker finds a vacancy is an increasing function of labor market tightness, $\psi_t^{hj} = f(\theta_t^j)$, while the probability that a job vacancy is matched with an unemployed worker is a decreasing function of tightness, $\psi_t^{fj} = f(\theta_t^j)/\theta_t^j$.

In each period, jobs are destroyed at a constant fraction σ^j and m_t^j new matches are formed. The law of motion of employment n_t^j is then given by,

$$n_{t+1}^j = (1-\sigma^j) n_t^j + m_t^j = (1-\sigma^j) n_t^j + \psi_t^{hj} u_t^j. \tag{2.2}$$

Using the vacancy-filling probability, we obtain an equivalent expression,

$$n_{t+1}^j = (1-\sigma^j) n_t^j + \psi_t^{fj} v_t^j. \tag{2.3}$$

2.2.2 Household

Next, we present the structure of the household side in the model and the corresponding optimization problem.

Utility function and budget constraint

The representative household consists of a continuum of infinitely lived members. Utility is derived from consumption c_t and from leisure, which corresponds to the fraction of members out of the labor force l_t. The instantaneous utility function is given by,

$$U(c_t, l_t) = \frac{c_t^{1-\eta}}{1-\eta} + \Phi \frac{l_t^{1-\varphi}}{1-\varphi},$$

where η is the inverse of the intertemporal elasticity of substitution, $\Phi > 0$ is the relative preference for leisure and φ is the inverse of the Frisch elasticity of labor supply. At any point in time, a fraction n_t^M (n_t^S) of the household's members are employees in the manufacturing (service) sector. The household chooses the fraction of the unemployed actively searching for a job u_t versus those who are out of the labor force enjoying leisure l_t so that

$$n_t^M + n_t^S + u_t + l_t = 1. \tag{2.4}$$

Of the unemployed u_t, the household chooses the fraction of job seekers who look for a job in the manufacturing sector s_t while the remaining $1 - s_t$ search in services, so that

$$u_t = s_t u_t + (1 - s_t)u_t = u_t^M + u_t^S, \tag{2.5}$$

where $u_t^M \equiv s_t u_t$ and $u_t^S \equiv (1 - s_t)u_t$. The household accumulates assets, evolving over time according to

$$k_{t+1} = i_t + (1 - \delta)k_t, \tag{2.6}$$

where i_t is investment and δ is a constant depreciation rate. The household budget constraint is given by,

$$c_t + i_t \leq r_t k_t + w_t^M n_t^M + w_t^S n_t^S + \bar{b}_t u_t - T_t + \Pi_t^M + \Pi_t^S, \tag{2.7}$$

where w_t^j is the real wage in each sector, r_t is the real return on assets, $\bar{b}_t$ is the unemployment benefit (see Section 2.4), T_t refers to lump-sum taxes that adjust to satisfy the government budget, i.e. $\bar{b}_t u_t = T_t$, and Π_t^j for $j = M, S$ denotes dividends received from ownership of the firms. We model the unemployment benefit as a share ϖ of the average wage in the economy through the function $\bar{b}_t = \varpi \frac{(w_t^M n_t^M + w_t^S n_t^S)}{n_t^M + n_t^S}$.

The optimization problem

The household maximizes the expected lifetime utility subject to equations (2.1), (2.2), (2.4), (2.5), (2.6), and (2.7) (for details, see the Online Appendix). Denoting by $\lambda_{n^M t}$, $\lambda_{n^S t}$, and λ_{ct} the Lagrange multipliers on equations (2.2) for $j = S, M$ and (2.7), the first-order conditions with respect to c_t, k_{t+1}, n_{t+1}^M, n_{t+1}^S, u_t and s_t are given by,

$$c_t^{-\eta} = \lambda_{ct}, \tag{2.8}$$

$$\lambda_{ct} = \beta E_t \left[\lambda_{ct+1}(1 - \delta + r_{t+1})\right], \tag{2.9}$$

$$\lambda_{n^{M_t}} = \beta E_t \left[-\Phi l_{t+1}^{-\varphi} + c_{t+1}^{-\eta} w_{t+1}^{M} + \lambda_{n^{M_{t+1}}}(1 - \sigma^{M})\right], \tag{2.10}$$

$$\lambda_{n^{S_t}} = \beta E_t \left[-\Phi l_{t+1}^{-\varphi} + c_{t+1}^{-\eta} w_{t+1}^{S} + \lambda_{n^{S_{t+1}}}(1 - \sigma^{S})\right], \tag{2.11}$$

$$\Phi l_t^{-\varphi} - \lambda_{n^M t} \psi_t^{hM} s_t - \lambda_{n^S t} \psi_t^{hS}(1 - s_t) = \lambda_{ct} \bar{b}_t, \tag{2.12}$$

$$\lambda_{n_t^M} \psi_t^{hM} = \lambda_{n_t^S} \psi_t^{hS}. \tag{2.13}$$

Equations (2.8) and (2.9) are the non-arbitrage conditions for the returns to consumption and capital. Equations (2.10) and (2.11) relate the expected marginal value of being employed in each sector to the utility loss from the reduction in leisure, the wage, and the continuation value, which depends on the separation probability. Equation (2.12) states that the value of being unemployed (rather than enjoying leisure) should equal the marginal utility from leisure minus the expected marginal values of being employed in each sector, weighted by the respective job finding probabilities and shares of job seekers. Equation (2.13) states the choice of the share s_t is such that the expected marginal values of being employed, weighted by the job finding probabilities, are equal in the two sectors. Notice that the marginal value to the household of an additional member employed in each sector is given by,

$$V_{n^{M_t}}^{h} = -\Phi l_t^{-\varphi} + \lambda_{ct} w_t^{M} + (1 - \sigma^{M}) \lambda_{n^M t}, \tag{2.14}$$

$$V_{n^{S_t}}^{h} = -\Phi l_t^{-\varphi} + \lambda_{ct} w_t^{S} + (1 - \sigma^{S}) \lambda_{n^S t}. \tag{2.15}$$

2.2.3 Production

We now turn to the structure of the production side in the economy and present the optimization problem of the firms in the two sectors.

Final good

There are three goods produced in the economy. These include two intermediate goods, namely manufacturing and service goods (M_t and S_t), which are combined in the production of the final good Y_t according to a CES technology,

$$Y_t = \left[\gamma M_t^{\frac{\chi-1}{\chi}} + (1-\gamma) S_t^{\frac{\chi-1}{\chi}}\right]^{\frac{\chi}{\chi-1}}, \tag{2.16}$$

where $0 < \gamma < 1$ denotes the weight attached to the manufacturing good versus the service good and χ is the elasticity of substitution.

The three goods are sold in competitive markets and we assume that the final good is the numeraire. Therefore, the prices of the sectoral goods equal the marginal products,

$$p_t^M = \frac{\partial Y_t}{\partial M_t} = \gamma \left(\frac{Y_t}{M_t}\right)^{\frac{1}{\chi}}, \tag{2.17}$$

$$p_t^S = \frac{\partial Y_t}{\partial S_t} = (1-\gamma) \left(\frac{Y_t}{S_t}\right)^{\frac{1}{\chi}}. \tag{2.18}$$

Manufacturing intermediate good

The manufacturing good is produced by combining capital k_t with employment n_t^M,

$$M_t = \left[\zeta k_t^{\frac{\alpha-1}{\alpha}} + (1-\zeta)(n_t^M)^{\frac{\alpha-1}{\alpha}}\right]^{\frac{\alpha}{\alpha-1}}, \tag{2.19}$$

where ζ denotes the weight attached to capital versus labor and α is the elasticity of substitution.

An increase in ζ makes output more capital-intensive at the expense of labor, representing in our setup an increased robot adoption (automation). The microeconomic foundations are derived by Acemoglu and Restrepo, 2018 in a framework where a continuum of tasks is used in production. Automation in that context is interpreted as a shift in the share of tasks that can be produced with capital. Acemoglu and Restrepo, 2018 show how one can aggregate the tasks to establish a production function with aggregate capital and labor inputs (see also the discussion in Bergholt, Furlanetto, and Faccioli, 2020).

Firms maximize the discounted expected value of future profits subject to the technology and the law of motion of employment (2.2). That is, they take the number of workers currently employed n_t^j as given and choose the number of vacancies to post v_t^j so as to employ the desired number of workers next period n_{t+1}^j. The firm also chooses the amount of capital to demand. The manufacturing firm solves the problem,

$$Q^M(n_t^M) = \max_{v_t^M, k_t} \Big\{ p_t^M M_t - w_t^M n_t^M - r_t k_t - \kappa^M v_t^M + E_t \left[\Lambda_{t,t+1} Q^M(n_{t+1}^M) \right] \Big\}, \tag{2.20}$$

where κ^M denotes the marginal cost of posting a vacancy. As the household owns the firm, the term $\Lambda_{t,t+1} = \beta\lambda_{ct+1}/\lambda_{ct}$ refers to the household's stochastic discount factor in which λ_{ct} denotes the Lagrange multiplier for the household budget constraint and β is the household's discount factor.

The first-order conditions with respect to v_t^M and k_t are,

$$\kappa^M = \psi_t^{fM} \times E_t \Lambda_{t,t+1} \left[p_{t+1}^M (1-\zeta) \left(\frac{M_{t+1}}{n_{t+1}^M} \right)^{\frac{1}{\alpha}} - w_{t+1}^M + \frac{(1-\sigma^M)\,\kappa^M}{\psi_{t+1}^{fM}} \right], \tag{2.21}$$

$$r_t = p_t^M \cdot \zeta \left(\frac{M_t}{k_t} \right)^{\frac{1}{\alpha}}. \tag{2.22}$$

Equation (2.21) states that the marginal cost of hiring a worker should equal the expected marginal benefit subject to the vacancy-filling probability. The latter includes the net value of the marginal product of labor, where ζ enters with a negative sign, minus the wage plus the continuation value. Equation (2.22) states that the return on capital is equal to the value of its marginal product, where ζ enters with a positive sign.

The value of the marginal job for the firm is given by,

$$V_{n^M t}^f = p_t^M (1-\zeta) \left(\frac{M_t}{n_t^M} \right)^{\frac{1}{\alpha}} - w_t^M + \frac{(1-\sigma^M)\,\kappa^M}{\psi_t^{fM}}. \tag{2.23}$$

Service intermediate good

In the service sector, we assume a simple production function with labor only,

$$S_t = B(n_t^S)^b, \tag{2.24}$$

where B denotes total factor productivity (TFP) and b is the degree of returns to scale.

A firm operating in this sector solves the following problem,

$$Q_t^S(n_t^S) = \max_{v_t^S} \Big\{ p_t^S S_t - w_t^S n_t^S - \kappa^S v_t^S + E_t \left[\Lambda_{t,t+1} Q_{t+1}^S(n_{t+1}^S) \right] \Big\}. \tag{2.25}$$

The first-order condition is,

$$\kappa^S = \psi_t^{fS} \times E_t \Lambda_{t,t+1} \left[p_{t+1}^S b \frac{S_{t+1}}{n_{t+1}^S} - w_{t+1}^S + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi_{t+1}^{fS}} \right]. \tag{2.26}$$

The value to the firm of a marginal job is given by,

$$V_{n^S t}^f = p_t^S b \frac{S_t}{n_t^S} - w_t^S + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}}. \tag{2.27}$$

2.2.4 Wage bargaining

Following standard practice, the Nash bargaining problem in each sector is to maximize the weighted sum of log surpluses,

$$\max_{w_t^j} \left\{ \left(1-\vartheta^j\right) \ln V_{n^j t}^h + \vartheta^j \ln V_{n^j t}^f \right\},$$

where ϑ^j denotes the bargaining power of firms and $V_{n^j t}^h$, $V_{n^j t}^f$ have been defined above. The first-order condition with respect to w_t^j is

$$\vartheta^j V_{n^j t}^h = \left(1-\vartheta^j\right) \lambda_{ct} V_{n^j t}^f.$$

Through the derivations shown in the Online Appendix, we obtain the equilibrium values for wages in the two sectors,

$$w_t^M = \left(1-\vartheta^M\right) \left(p_t^M (1-\zeta) \left(\frac{M_t}{n_t^M}\right)^{\frac{1}{\alpha}} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi_t^{fM}} \right) + \frac{\vartheta^M}{\lambda_{ct}} (\Phi l_t^{-\varphi} - \left(1-\sigma^M\right) \lambda_{n^{M_t}}), \tag{2.28}$$

$$w_t^S = \left(1-\vartheta^S\right) \left(p_t^S b \frac{S_t}{n_t^S} + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}} \right) + \frac{\vartheta^S}{\lambda_{ct}} (\Phi l_t^{-\varphi} - \left(1-\sigma^S\right) \lambda_{n^{S_t}}). \tag{2.29}$$

2.2.5 Resource constraint

The final good is used for consumption and investment, and also to cover vacancy costs.

$$Y_t = c_t + i_t + \kappa^M v_t^M + \kappa^S v_t^S. \tag{2.30}$$

The derivation of the resource constraint is shown in the Online Appendix.

2.3 Relative Labor Demand and Labor Supply in Equilibrium

In this section, we establish the equilibrium relationship between relative labor demand and relative labor supply in the two sectors.

Proposition 1. *In equilibrium, the sectoral ratio of labor market tightness depends only on the bargaining power and vacancy costs in the two sectors,*

$$\frac{\theta_t^M}{\theta_t^S} = \frac{\vartheta^M}{(1-\vartheta^M)} \frac{(1-\vartheta^S)}{\vartheta^S} \cdot \frac{\kappa^S}{\kappa^M}$$

Proof. See Appendix A. □

Proposition 1 establishes that the *relative* labor market tightness of the two sectors is constant in equilibrium and characterizes its level. Asymmetric bargaining power and/or vacancy costs introduce a wedge in tightness between the two sectors. Conversely, if both the bargaining power and vacancy costs are symmetric, tightness is equal in the two sectors. The derivation of Proposition 1 (see the Appendix) builds on Ravn, 2008, where a relationship between tightness and the marginal utility of consumption is derived in a one-sector search and matching model with endogenous participation.

The relationship between relative labor supply and relative labor demand directly follows from the proposition,

$$\underbrace{\frac{s}{1-s} \equiv \frac{u^M}{u^S}}_{\text{Relative labor supply}} = \frac{(1-\vartheta^M)}{\vartheta^M} \frac{\vartheta^S}{(1-\vartheta^S)} \frac{\kappa^M}{\kappa^S} \cdot \underbrace{\frac{v^M}{v^S}}_{\text{Relative labor demand}}$$

For a given level of relative labor demand (which depends, among others, on the degree of automation ζ), the pool of job seekers in manufacturing increases with the relative (i) bargaining power of workers and (ii) vacancy cost. In the second case, an increased pool of unemployed is required to compensate for the higher vacancy cost when firms decide about new vacancies so that the level of labor demand is sustained in equilibrium.

Finally, notice that the household decides how to allocate job seekers by comparing the discounted expected values of searching in the two sectors, $\psi^{j,h}\beta E_t \left[V^h_{n^j{t+1}}\right]$, which, in turn, is equal to the probability of finding a job times the discounted expected value of being employed. The optimal value s^* is given by,

$$s^* = \begin{cases} 1 & \psi_t^{M,h} \beta E_t \left[V^h_{n^{M_{t+1}}} \right] > \psi_t^{S,h} \beta E_t \left[V^h_{n^{S_{t+1}}} \right] \\ s^* \in (0,1) & \psi_t^{M,h} \beta E_t \left[V^h_{n^{M_{t+1}}} \right] = \psi_t^{S,h} \beta E_t \left[V^h_{n^{S_{t+1}}} \right] \\ 0 & \psi_t^{M,h} \beta E_t \left[V^h_{n^{M_{t+1}}} \right] < \psi_t^{S,h} \beta E_t \left[V^h_{n^{S_{t+1}}} \right] \end{cases}$$

In general equilibrium, we can rule out the two corner solutions. If $s^* = 1$ and all the unemployed search in manufacturing, there is no production in services. Yet, as long as the two sectoral goods are not perfect substitutes in the final good production, the marginal product of the service good becomes infinite, leading to an infinite wage, which is incompatible with zero labor supply in this sector. If $s^* = 0$ and all the unemployed search in services, there is no production in manufacturing. Yet, as long as capital and labor are not perfect substitutes in manufacturing production, the marginal product of labor in manufacturing becomes infinite, which, again, is incompatible with a zero supply of labor in that sector. Therefore, the only possible solution is $s^* \in (0,1)$.

2.4 Calibration Strategy

In this section, we describe the calibration of the initial steady state, which we take to refer to the start year 1994 in the analysis of Dauth, Findeisen, Suedekum, and Woessner, 2021. We calibrate the model annually to the German economy. Table 2.1 summarizes our calibration.

Household. We use the data set built by Jordà, Knoll, Kuvshinov, Schularick, and Taylor, 2019 to compute the return to capital r in Germany, equal to 5% in 1994. We set the capital depreciation rate δ equal to 4%. To choose the value for the discount factor, we use the Euler equation in the steady state, $\beta = 1/(1 + r - \delta)$. For the inverse elasticity of the intertemporal substitution η, much of the literature uses econometric estimates between 0 and 2 (see, e.g., Hansen and Singleton, 1983). The estimated aggregate Frisch elasticity for Germany varies between 0.85 and 1.06 in a micro panel of men in Germany from 2000 to 2013 used by Kneip, Merz, and Storjohann, 2020. We thus set the Frisch elasticity to 0.85 ($\phi = 2$). We have performed sensitivity analysis for different values $\phi = 4, 6$ (see the Online Appendix and footnote 13).

We calibrate the relative utility weight for leisure Φ to target a participation rate of 70%.

Production. To calibrate the parameters of the aggregate production function, we follow Iftikhar and Zaharieva, 2019, setting the share of manufacturing output γ to 0.33 and the elasticity of substitution between the manufacturing and the service goods χ to 0.3. In the manufacturing production function, we set the elasticity of substitution between capital and labor α to 0.6. Based on a meta-regression sample, Knoblach, Roessler, and Zwerschke, 2020 estimate a long-run elasticity for the aggregate economy in the range of 0.45-0.87, noting that most industrial estimates do not deviate significantly from the estimate for the aggregate economy. Our calibrated value is also in line with Oberfield and Raval, 2020 who find the US manufacturing sector's aggregate elasticity to be in the range of 0.5-0.7. Most of the literature estimates constant (or slightly decreasing) returns at the industry level (see, e.g., Ahmad, Fernald, and Khan, 2019 and Maioli, 2004). Therefore, we set the parameter b, in the production function of the service good, equal to one. We also normalize the TFP parameter B to one.

Labor Markets. To calibrate the parameters for the bargaining power of firms in each sector, we take weighted averages of the estimates for high-skill and low-skill workers in Iftikhar and Zaharieva, 2019. A lower bargaining power for workers in the service sector is in line with the empirical evidence that service workers get a lower fraction of output produced in their sector, leading to a mild wage premium in manufacturing of around 2% in our calibration. The same authors estimate the average job duration rate in Germany to be 12.25 years, so we set the destruction rate in both sectors as $\sigma = 1/12.25 = 0.08$. We set the gross replacement rate ϖ equal to 0.6.[4] For the vacancy cost parameter, we set in both sectors $\kappa = 0.1$, which implies that vacancy costs represent around 20% of the average wage. Using aggregate data of the Federal Employment Agency, Iftikhar and Zaharieva, 2019 estimate the elasticity of the matching function with respect to vacancies to be 0.54, which is close to 0.5, often assumed in the search and matching literature. Their estimate for the matching efficiency parameter is 0.58.

[4]According to the OECD, the standard rates in Germany after 2000 are 60% of the previous earnings net of tax.

	DESCRIPTION	VALUE	TARGET/SOURCE
HOUSEHOLD			
β	Discount factor	0.99	Return to capital, 5%
δ	Depreciation rate	0.04	Standard calibration
Φ	Relative utility from leisure	0.8	Participation Rate, 70%
ϕ	Inverse Frisch elasticity of labor supply	2	Kneip, Merz, and Storjohann, 2020
η	Inverse elasticity of intertemporal substitution	2	Hansen and Singleton, 1983
PRODUCTION			
γ	Share of manufacturing in total output	0.33	Iftikhar and Zaharieva, 2019
χ	Manufacturing-services elasticity of substitution	0.3	Iftikhar and Zaharieva, 2019
α	Capital-labor elasticity of substitution	0.8	Knoblach, Roessler, and Zwerschke, 2020
B	TFP in services	1	normalization
b	Degree of returns to scale in services	1	Ahmad, Fernald, and Khan, 2019
LABOR MARKET			
θ^M, θ^S	Bargaining power of firms	0.43, 0.6	Iftikhar and Zaharieva, 2019
μ_1	Matching efficiency	0.58	Iftikhar and Zaharieva, 2019
μ_2	Elasticity of matching to vacancies	0.46	Iftikhar and Zaharieva, 2019
σ	Separation rate	0.08	Iftikhar and Zaharieva, 2019
κ	Vacancy cost	0.1	Share of the average wage, 20%
ϖ	Replacement rate	0.6	OECD data

TABLE 2.1: Calibration

2.5 Automation and Sectoral Reallocation

In this section, we present the main results of our quantitative analysis. First, we discuss steady-state comparative statics with respect to an increase in the degree of automation ζ. Then, we show that the model can replicate the magnitude of the decline in the ratio of manufacturing employment to service employment in Germany between 1994 and 2014.

2.5.1 Analysis Across Steady States

Figure 2.4 depicts results for the steady-state levels of the main variables of the model for $0.25 < \zeta < 0.5$, which is an empirically relevant interval.

Sectoral Reallocation of Output. A higher degree of automation ζ corresponds in our model to an increased (decreased) capital (labor) intensity of manufacturing production. Since the steady-state return to capital is constant, while the steady-state return to labor can freely adjust, the capital

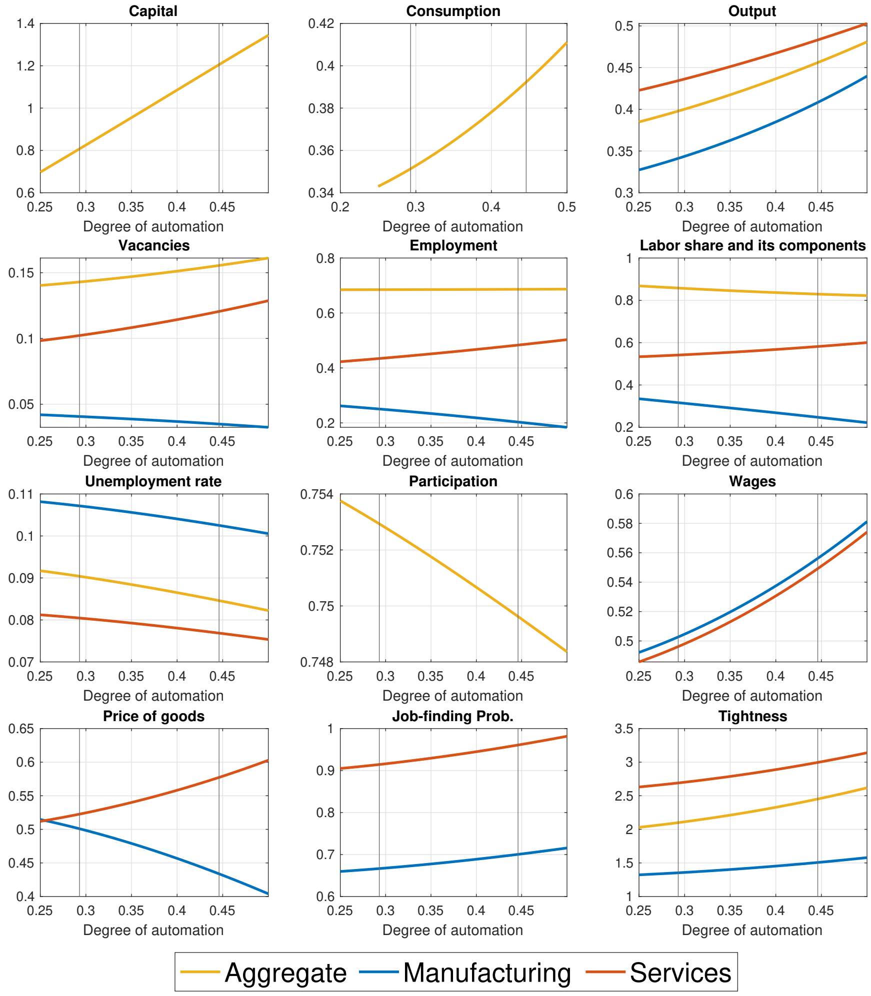

FIGURE 2.4: Steady-state effects of automation in a two-sector economy

Note: The y-axis shows steady-state levels. In each plot, the two vertical lines refer to the two steady states that we compare in Table 2.2. In the labor share plot, the blue and red lines refer to the share in total output of employment compensation in manufacturing and services, respectively.

increase due to a higher ζ dominates the labor decline. Therefore, manufacturing output increases.[5] In turn, output in services also increases since the two sectoral goods are complements in the production of the final good *(sectoral complementarity effect)*. In addition, as the total output increases, the household who is the owner of capital and firms enjoys a higher income and

[5]The effect of an increase in ζ on manufacturing output M is expressed by the derivative:

$$\frac{\partial M}{\partial \zeta} = \frac{1}{\alpha} M^{(1-\alpha)} \left[k^{\alpha} - (n^M)^{\alpha} + \zeta \alpha \frac{\partial k}{\partial \zeta} + (1-\zeta)\alpha \frac{\partial n^M}{\partial \zeta} \right]$$

An increase in ζ induces an accumulation of capital ($\frac{\partial k}{\partial \zeta} > 0$) and a decrease in employment ($\frac{\partial n^M}{\partial \zeta} > 0$). The difference $k^{\alpha} - (n^M)^{\alpha}$ also matters for which effect dominates. If the initial value of ζ is sufficiently low, the steady-state capital stock k is relatively low and labor n^M is relatively more important in the production, leading to a decrease in manufacturing output.

demands more of the service good *(income effect)*. Therefore, the economy experiences an aggregate output expansion. Overall, a higher ζ increases the steady-state ratio of manufacturing to service output M/S and decreases the relative price of the manufacturing good (see equations (2.17) and (2.18)).[6]

Consumption, Participation, and Labor Share. The positive income effect for the household explains the increase in consumption and the decrease of participation. Automation has a negative effect on the aggregate labor share, which is driven by the manufacturing sector and is in line with the literature findings on the importance of the automation mechanism for a countercyclical labor share (see, e.g., Bergholt, Furlanetto, and Faccioli, 2020 and Leduc and Liu, 2020b).

Sectoral Reallocation of Labor. Vacancies in the manufacturing sector decrease. Automation affects labor demand in manufacturing through two competing channels: (a) production becomes less labor-intensive, which tends to decrease employment *(labor-intensity channel)* and (b) since capital and labor are complements, the increase in capital tends to increase labor demand *(capital-labor complementarity effect)*. Vacancies in services increase due to the *sectoral complementarity effect* and the positive *income effect*. Total vacancies increase as well.

The number of unemployed searchers drops in the manufacturing sector as households reduce participation and reallocate job search towards services. The unemployment rate drops in the service sector too, but the share of searchers increases (see blue line in Figure 2.5). Total unemployment falls.

Labor market tightness increases in both sectors. The effect on the hiring rates follows from the fact that they are a positive function of tightness (while the opposite holds for vacancy-filling rates). The impact of automation on wages in both sectors is positive, consistently with the decrease in the vacancy-filling probabilities.

Following the sectoral reallocation of labor, employment increases in services and falls in manufacturing in such a way that aggregate employment remains relatively constant, in line with the empirical evidence in Dauth, Findeisen, Suedekum, and Woessner, 2021. The pattern matches well the one observed in Figure 2.1.[7]

[6]Recall that capital serves as input only in manufacturing production.

[7]To also match the levels, we would need to add capital in the service sector.

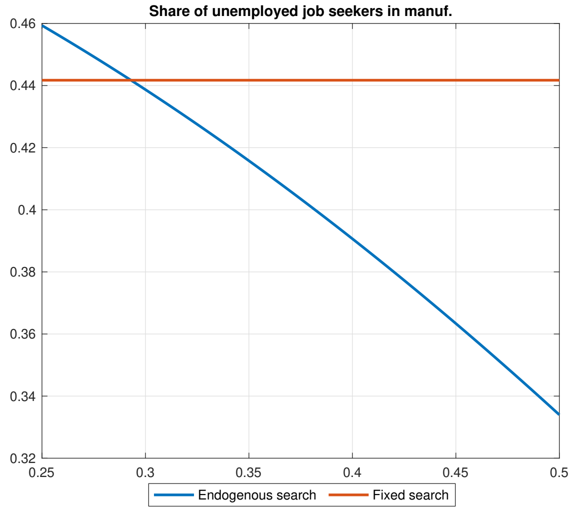

FIGURE 2.5: The steady-state effect of automation on searchers' share in manufacturing

Note: The y-axis shows steady-state levels. The blue line refers to the baseline model, whereas the red line refers to a model variant where the sectoral allocation of job seekers is kept fixed.

In sum, labor markets adjust to automation through vacancy creation, sectoral reallocation of the unemployed, and participation. The findings also highlight the expansionary effects of automation in the economy, namely the aggregate output expansion and unemployment reduction.

2.5.2 The Decline of the Sectoral Labor Ratio from 1994 to 2014

The model can also replicate the magnitude of the decline in the ratio of manufacturing employment to service employment in Germany. Specifically, we take from the data the values of the capital share in manufacturing in 1994 and 2014, which are the start and end years in the empirical analysis in Dauth, Findeisen, Suedekum, and Woessner, 2021.[8] Following Iftikhar and Zaharieva, 2019, we define our manufacturing sector as the aggregate of Industries A-F in the German WZ08 industry classification. Moreover, robots are predominantly employed in these industries. Then, we compute the values of the degree of automation ζ that generate these two values in our model. For a manufacturing capital share equal to 0.24 in 1994, we find that the implied value of ζ is 0.29, while for a capital share equal to 0.36 in 2014 the implied value of ζ is 0.44 (see Table 2.2).

[8] EUKLEMS defines the capital share as the ratio of capital services to the value added.

Next, we examine the steady-state values for the ratio of manufacturing employment to service employment for these two values of ζ. The model predicts a decline of 27% in the ratio of manufacturing employment to service employment, which is reasonably close to the one found in the aggregate data for the German economy (32%). Using a local labor market approach, Dauth, Findeisen, Suedekum, and Woessner, 2021 find that, on average, employment in manufacturing falls by 16.86%, while non-manufacturing employment increases by 3.74%.[9] This implies that the weighted average of the sectoral labor ratio over the 402 local labor markets analyzed in their paper decreases by 19.85%.[10] Therefore, our model's prediction about a decline of 27% lies between the value estimated using our aggregated data (32%) and the statistics for local labor markets (nearly 20%) in Dauth, Findeisen, Suedekum, and Woessner, 2021.

Variable	Notation	1994	2014	Change: model	Change: data
Degree of automation	ζ	0.293	0.446	52%	N/A
Manufacturing capital share	$\frac{rK}{p^M M}$	0.236	0.340	44%	44%
Labor ratio: manuf./service	$\frac{n^M}{n^S}$	0.576	0.420	-27%	-32%

TABLE 2.2: Comparison of two steady states (Germany 1994 and 2014)

2.6 What Determines the Extent of Sectoral Reallocation?

In this section, we investigate the role of key parameters and features of the model, namely (i) the elasticity of substitution between the sectoral goods, (ii) the elasticity of substitution between capital and labor, and (iii) the sectoral mobility of job seekers.

2.6.1 Elasticities of Substitution

Between the Sectoral Goods. The elasticity of substitution between the sectoral goods χ matters both for the sectoral reallocation of output and for the

[9]See Table 1 in Dauth, Findeisen, Suedekum, and Woessner, 2021.

[10]We computed the rate of change in $\frac{n^M}{n^S}$ as: $\widehat{\frac{n^M}{n^S}} = \frac{1+\widehat{n^M}}{1+\widehat{n^S}} - 1$, where $\widehat{x} = \frac{x_{2014}-x_{1994}}{x_{1994}}$.

sectoral reallocation of labor. Figure 2.6 compares the change in key sectoral ratios of variables as the degree of automation ζ increases from an initial steady state (with $\zeta = 0.25$) for a higher elasticitity χ and for our benchmark calibration. Additional variables and the same results in levels of these ratios are included in the Online Appendix. Relative to the baseline calibration ($\chi = 0.3$), when we increase the elasticity ($\chi = 1.5$), the sectoral output ratio M/S changes by more due to automation because it is easier now to substitute services by manufacturing intermediate goods in the final good production.[11] Consequently, an increase in χ mitigates the effect of automation on the sectoral reallocation of labor, vacancies, and job seekers (see the plots of the sectoral labor ratios n^M/n^S, v^M/v^S, and u^M/u^S). In line with these results, the drop in the wage premium in manufacturing w^M/w^S becomes less pronounced.

Between Capital and Labor. The elasticity of substitution between capital and labor matters for the sectoral reallocation of labor. Figure 2.6 also depicts results for a lower elasticitity of substitution between capital and labor α. Through the capital-labor complementarity channel, a decrease in α tends to dampen the automation-driven sectoral reallocation of vacancies, job seekers, and labor as well as the drop in the wage premium in manufacturing (see the plots of the sectoral labor ratios v^M/v^S, u^M/u^S, n^M/n^S, and w^M/w^S). It also affects the sectoral price ratio (p^M/p^S) reaction to automation.

2.6.2 Sectoral Mobility of Job Seekers

Next, we explore the extent to which shutting down the reallocation of job seekers between the two sectors affects our findings. We examine the comparative statics with (a) endogenous sector-specific search and (b) fixed sectoral shares of job seekers by keeping the share of searchers in manufacturing s equal to the value it attains endogenously in the initial calibrated steady state of Section 5.2 $\zeta = 0.293$ (see Figure 2.5). In other words, equation (2.13) is no longer used. Hence, although the number of employees per sector can evolve separately through the dynamics of vacancy postings, matches, and participation, households cannot freely reallocate job seekers between sectors.

With a fixed sectoral allocation of job seekers, as we move from a steady state with $\zeta = 0.293$ to a steady state with $\zeta = 0.446$ (in line with Table 2.2),

[11] As shown in the Online Appendix, even when the two goods are imperfect substitutes ($\chi = 1.5$), output in services increases due to the income effect.

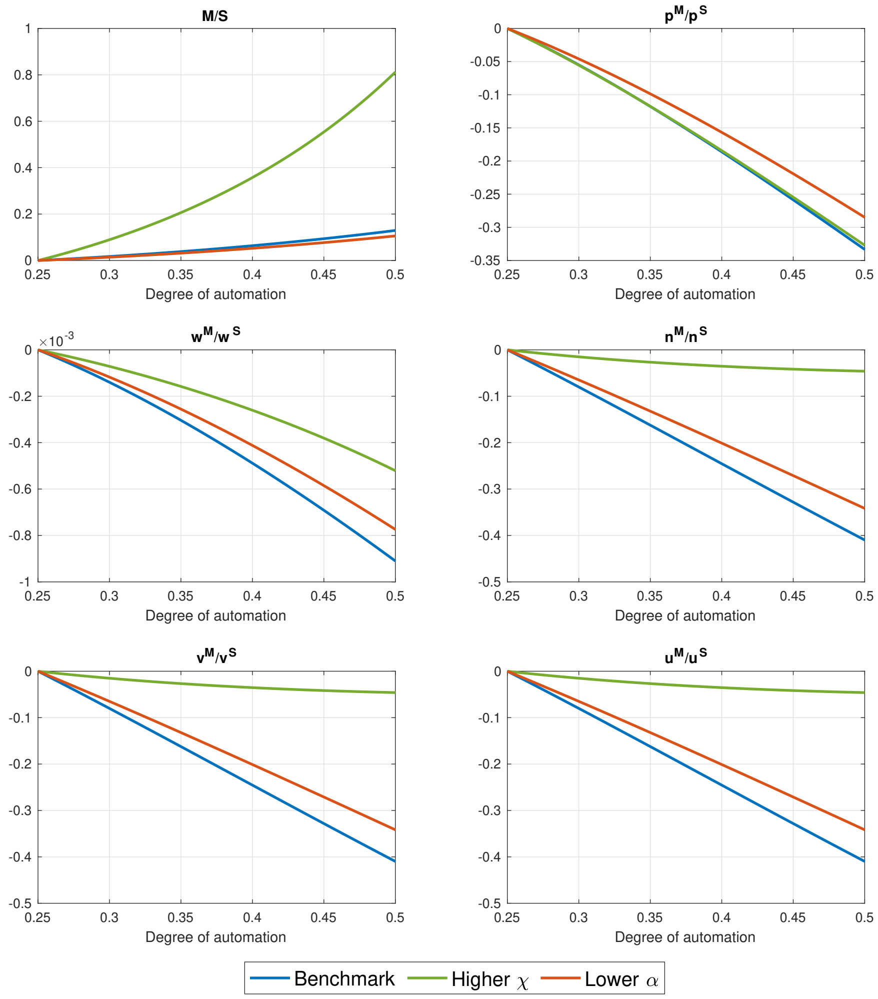

FIGURE 2.6: Steady-state effects of automation in a two-sector economy: Different elasticities of substitution between capital and labor ($\alpha = 0.7$) and between the two goods ($\chi = 1.5$)

Note: All the plotted variables are normalized to 0 *in the steady state with* $\zeta = 0.25$. *We denote the ratios of manufacturing to services variables as follows:* M/S *for output,* p^M/p^S *for prices,* w^M/w^S *for wages,* n^M/n^S *for labor,* v^M/v^S *for vacancies, and* u^M/u^S *for job seekers.*

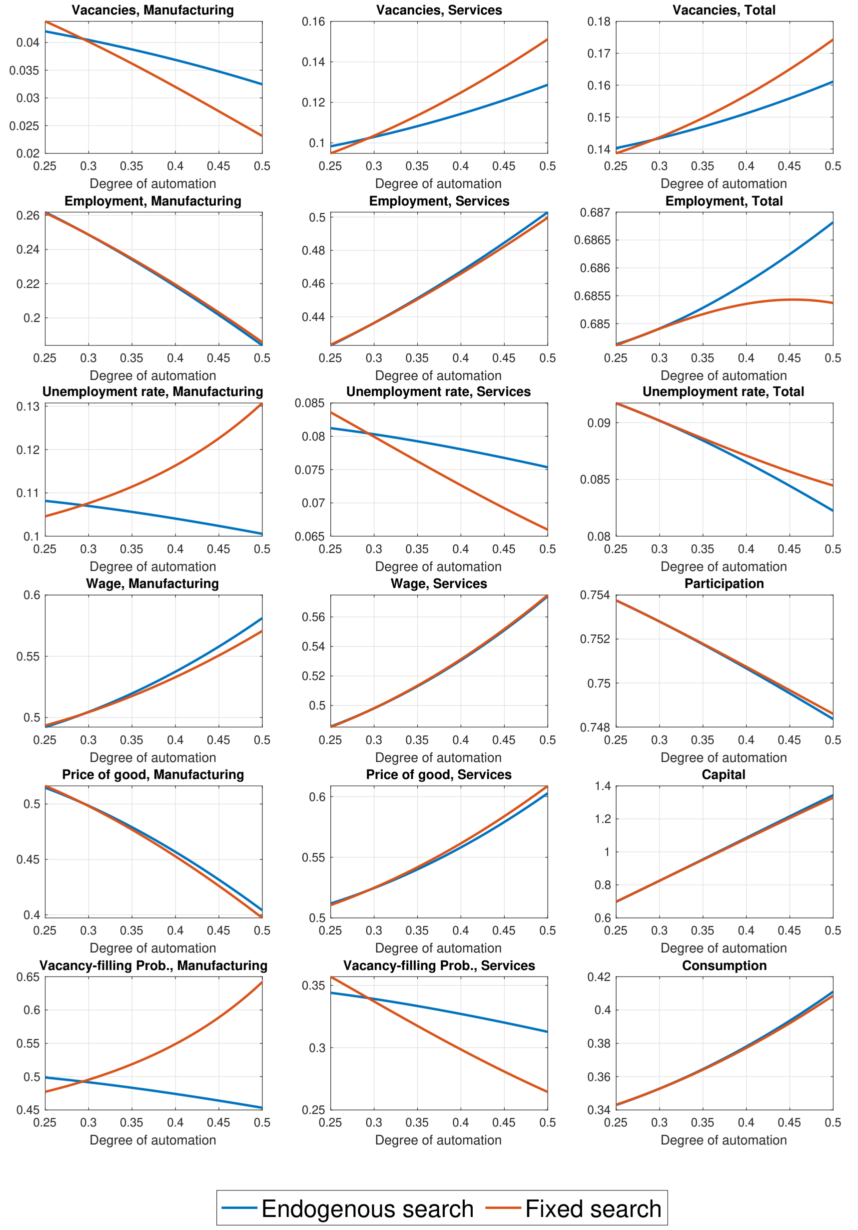

FIGURE 2.7: Steady-state effects of automation with and without sectoral mobility

Note: The y-axis shows steady-state levels. The blue line refers to the baseline model, whereas the red line refers to a model variant where the sectoral allocation of job seekers is kept fixed.

total employment changes even less than with endogenous allocation (see Figure 2.7).[12] If job seekers cannot move, the unemployment rate in manufacturing increases with ζ. At the same time, the negative effect on the unemployment rate in services becomes sharper since without the reallocation of job seekers there is less competition in this labor market. Yet, differences are not very large in magnitude.

[12]Figure 2.7 omits the output and labor share variables as the differences between the two model variants are minimal. Results are available upon request.

The sectoral mobility of job seekers also matters for the effect of automation on vacancies: under fixed search, the impact on manufacturing vacancies becomes more negative, while the positive effect on vacancies in services is reinforced. This result is explained by the effects on sectoral prices, which, in turn, suggest that the sectoral reallocation of output is somewhat smaller than in the baseline model.[13]

2.7 Conclusion

The paper studies the sectoral impact of automation through the lens of a general equilibrium model with matching frictions, endogenous participation, and two production sectors. In the model, as in empirical evidence from Germany (see Dauth, Findeisen, Suedekum, and Woessner, 2021), automation induces firms to create fewer new vacancies and job seekers to search less in the robot-exposed sector. Analysis across steady states shows that the reduction in manufacturing employment from automation can be offset by the increased service employment, thus leaving aggregate employment unaffected. The model does a good job in replicating (a) qualitatively the empirical evolution of employment and employees' compensation (as a share of GDP) in manufacturing and services, and (b) the magnitude of the decline in the ratio of manufacturing employment to service employment from 1994 to 2014. Our findings also highlight the expansionary impact of automation on aggregate output.

Our model can be extended along several dimensions. For instance, the good produced in the automated sector (manufacturing) is, in fact, a tradable good. One plausible extension could therefore be to consider the sectoral impact of automation in an open economy framework. Another interesting avenue for further research would be to introduce skill heterogeneity and capital-skill complementarity (see, e.g., Dolado, Motyovszki, and Pappa, 2020). Such a setup could capture the idea that robots are complements with high-skill workers but substitutes for low-skill workers, allowing to study implications for inequality. We leave these topics for future research.

[13]In the Online Appendix, we also show results for different values of the parameter governing the Frisch elasticity of labor supply ($\phi = 4, 6$). A lower value of the Frisch elasticity (higher value of ϕ) matters for the steady-state levels of the variables but without affecting our main results.

Chapter 3

Common Ownership and Automation

With Dennis HUTSCHENREITER

Abstract

We study the effect of increasing common ownership on automation using a task-based model of automation. In a Cournot model we show that automation increases (decreases) with common ownership if the elasticity of capital supply is smaller (larger) than the elasticity of the labor supply function in the industry.

3.1 Introduction

Common ownership of publicly traded firms and the automation of tasks previously performed by workers are both rising phenomena in developed economies.

Backus, Conlon, and Sinkinson, 2019 build a measure of common ownership and document that it has tripled between 1980 and 2017 among the firms in the S&P 500. Over the same period, the 10 largest institutional investors have quadrupled their ownership in U.S. stocks and, by the end of 2016, they managed 26.5% of total equity assets (Ben-David, Franzoni, Moussawi, and Sedunov, 2016). Economic theory suggests that common ownership of firms competing in the same product market can reduce competition, pushing such markets toward monopolistic outcomes, with implications on consumers' welfare.[1] Azar, Raina, and Schmalz, 2019 and Azar, Schmalz, and Tecu, 2018 show that common ownership has indeed lead to anti-competitive behavior, causing higher prices and less output in the Airlines and Banking industries, respectively.

The global operational stock of industrial robots rose by about 65% between 2013 and 2018. Frey and Osborne, 2017 estimate that 47% of United States employment is at risk because of automation technologies, while Arntz, Gregory, and Zierahn, 2016 find that 9% of jobs are at risk in OECD countries. A growing number of papers study the effect automation on wages, employment, welfare and inequality. For example, Acemoglu and Restrepo, 2020 find that each robot installed in the US replaces six workers and Acemoglu, LeLarge, and Restrepo, 2020 find that robot adoption has negative effects on the French labor share and employment. On the other hand, Dauth, Findeisen, Suedekum, and Woessner, 2021 do not find adverse effect of robot penetration on total employment in Germany.

In this paper, we investigate the relationship between common ownership and automation. In particular, we study the effect of common ownership on firms' adoption decision of automation technologies.

To this end, we combine a Cournot duopoly model with a task-based model of production where capital and labor are used as inputs. Firms face an aggregate demand function and set quantities, while they are price takers in the inputs markets. Firms make decision taking into account the profit of the other firm, given an exogenous degree of common ownership.

[1] Backus, Conlon, and Sinkinson, 2019; Baker, 2015; Posner, Scott Morgan, and Weyl, 2016; Macho-Stadler and Verdier, 1991; Anton, Ederer, Gine, and Schmalz, 2018

We compute comparative statics with respect to the degree of common ownership and show that the effect on automation depends on the relationship between the elasticities of the supply functions. automation increase (decreases) with common ownership if the elasticity of the capital supply is smaller (larger) than the elasticity of the labor supply function in the industry.

The intuition behind this result is the following: increase in common ownership decreases the equilibrium level of production without affecting the cost minimization problem of the firm. In other words, the relative demand curve of the inputs of production does not react to changes in common ownership. As the demand for both inputs decrease, the associated decrease in prices determines which one between capital and labor is relatively cheaper. The effect on the price ratio ultimately determines the effect on the automation decision.

The remainder of this paper is organized as follows. Section 3.2 summarizes the relevant literature. Section 3.3 presents our model and in Section 3.4 the effect of common ownership on automation is analyzed. Section 3.5 concludes.

3.2 Related Literature

Our paper is related to a broad set of recent research in economics. First, it relates to the debate on the impact of common ownership on firms' objective function and actual firm behavior. Institutional ownership is an uprising matter in many countries and industries. Large institutional investors holding diversified portfolios lead to significant overlaps in the shareholder base of companies. In many industries in the U.S., funds as BlackRock, Vanguard, Fidelity or State Street are top shareholders in the main companies (Ben-David, Franzoni, Moussawi, and Sedunov, 2016). As another example, in 2008 BlackRock became the largest investor in German publicly listed companies, holding a value of around 20 billion U.S. dollars. By 2015 its holdings had more than quadrupled in value (Seldeslachts, Newham, and Banal-Estanol, 2017). The enormous growth in institutional investment, e.g. by pension funds, mutual funds, asset managers and endowments, that has not only been caused by the rise in passive investment strategies, has led to huge overlaps in the shareholder base, i.e., common ownership, of firms which are natural competitors in their markets. The effect of increasing common ownership on product market competition and consumer welfare as well as its implications for antitrust policy is investigated by academics in recent years (Backus, Conlon, and Sinkinson, 2019; Baker, 2015; Posner, Scott Morgan, and Weyl, 2016). However, the theoretical and empirical evidence of the impact of common ownership from the economic literature is still inconclusive.

The engagement of institutional investors in companies has possible pros and cons. On the one hand, institutional investors may foster innovation either by overcoming moral hazard problems through better monitoring (Aghion, Van Reenen, and Zingales, 2013) or, when they hold shares in the main companies of an industry, through the internalization of externalities in the presence of sufficiently large technology spillovers (López and Vives, 2019). In this regard, the paper by Anton, Ederer, Gine, and Schmalz, 2018 shows some evidence that common ownership on the firm-pair level might have positive or negative effects. Firms that produce products that are close in product market space (i.e., a high product market rivalry) also compete by means of costly investments in innovation. As common ownership leads firms to internalize the negative externality that a firm exerts on the other by innovating (business stealing effect) and, therefore, increasing its market share, firms with higher common ownership reduce their effort to innovate and thereby compete less aggressively. Contrarily, firms that are close in technology space (similar production technologies) may exert a positive externality on each other when innovating due to knowledge spillovers. common ownership will incentivize firms to partially internalize this positive externality leading to higher R&D investments. Therefore, they claim that the overall effect of common ownership depends on the relative strength of the effects caused by the closeness in technology space and product market rivalry and find some evidence for this using the measures of product market rivalry and technology spillovers proposed by Bloom, Schankerman, and Van Reenen, 2013.

On the other hand, the diversification practices of large institutional investors may result in anticompetitive behavior, causing higher prices and less output in some industries, as documented recently in the Airlines' and Banking industries (Azar, Raina, and Schmalz, 2019; Azar, Schmalz, and Tecu, 2018). Moreover, commonly owned firms seem to coordinate and collaborate more explicitly in the product market through within-industry joint ventures or strategic alliances (He and Huang, 2017). This coordination is a signal of softer competition among firms.

Macho-Stadler and Verdier, 1991 and Anton, Ederer, Gine, and Schmalz, 2018 study a potential mechanism through which common ownership leads to lesser competition. They show theoretically or empirically, respectively, that overlapping ownership may lead to a decrease in the alignment between managers' compensation with firm profits and to less relative performance pay. Thus, common owners give their managers less incentives to compete aggressively.

It has also been shown that common ownership plays a major role in mergers and acquisitions (M&As). On the one hand, Brooks, Chen, and Zeng, 2018, using various different measures of Institutional Cross-Ownership between acquirers and target firms, show that this type of common ownership leads to an increase in the probability of a merger of these firms and affects the outcomes of M&As, reducing deal premiums, increasing stock payment in M&A transactions, and lowering the completion probabilities of deals with negative acquirer announcement returns. Deals with high institutional cross-ownership are also found to have lower transaction costs which can be attributed to institutional investors' ability to decrease asymmetric information problems if they hold shares in both, the acquirer and the target. On the other hand, institutional owners may not only gain from M&As due to their holdings in acquirers and targets, but also through their ownership of rival firms, that are not involved in the acquisition deal. As economic theory suggests, e.g. in the symmetric Cournot model, the outsiders in the industry gain from a merger of two competitors. Anton, Azar, Gine, and Lin, 2020 find that acquirers' institutional shareholders ownership of outsider companies in the same industry is negatively associated with acquirer CAR and deal synergy, but positively associated with the completion probability of bad deals and that announcement losses are largely mitigated for the average acquirer shareholder when accounting for wealth effects on their stakes in the rival firms. Both of these studies confirm that common ownership effectively changes firm behavior.

Since common ownership is an economy-wide phenomenon, Azar and Vives, 2019; Azar and Vives, 2020 analyze the macroeconomic implications of common ownership developing models of oligopolistic markets with shareholder overlap in competing firms. They show that an increase in common ownership is associated with an decrease in the labor share, the capital share, rising profits and can also be used to explain the concentration of markets by shifting production from less to more productive firms in a setting in which competitors are heterogeneous in productivity and therefore partially explaining the trends described by Autor, Dorn, Katz, Patterson, and Van

Reenen, 2020 and De Loecker, Eeckhout, and Unger, 2020. The majority of paper in this literature focus on the effect of common ownership on the competition and on the product markets while we study the effect on the production inputs use.

A second strand of literature related to our paper is the study of the impact of automation on wages, employment, interest rates and income shares. In an intent to predict the future, Frey and Osborne, 2017 estimate that 47% of United States employment is at risk to be automated relatively soon, i.e., within the next two decades. Applying the methodology of Frey and Osborne, 2017 to more detailed task-based data, Arntz, Gregory, and Zierahn, 2016 find that on average 9% of jobs are automatable in OECD countries, ranging from 6% in Korea to 12% in Australia. Another branch of the automation literature tries to estimate the effects of robot penetration on employment and wages from historical data. On the one hand, Acemoglu and Restrepo, 2020 find a negative effect of robot penetration in the US labor markert, in particular they find that one more robot per thousand workers reduces the employment to population ratio by about 0.2 percentage points and wages by 0.42 percent. Acemoglu, LeLarge, and Restrepo, 2020 for a sample of french manufacturing firms find that the adoption of robots by a small set of large market share firms has overall negative effects on the labor share and employment. On the other hand, Dauth, Findeisen, Suedekum, and Woessner, 2021 do not find adverse effects on robot penetration for workers in Germany, but rather that automation leads to higher quality jobs for young employees and that young workers substitute away from vocational training towards colleges and universities in their education choices. We contribute to the automation literature by showing that common ownership has a potential impact on the incentives to adopt automation technologies.

3.3 Model

We consider a Cournot duopoly in which two firms, $j = 1, 2$, face an aggregate demand function for a homogeneous good and simultaneously set the quantity they want to produce in order to maximize their objective function. The aggregate inverse demand function for the good is given by

$$p = \begin{cases} a - Y, & \text{if } Y < a \\ 0, & \text{otherwise,} \end{cases} \tag{3.1}$$

where $a \in \mathbb{R}_{++}$ is the market size and $Y \in \mathbb{R}_{+}$ is the aggregate quantity produced by the two firms, i.e.,$Y = Y_1 + Y_2$.

O'Brien and Salop, 1999, López and Vives, 2019 show for a range of different ownership structures (e.g. silent financial interest, proportional control, and cross-ownership) that, when investors' stakes are symmetric, firms' objective function can be written as

$$\phi_j = \pi_j + \lambda \sum_{k \neq j} \pi_k, \tag{3.2}$$

where π_j is the profit of firm j and $\lambda \in [0,1]$ is the profit weight firm j puts on its rivals' profits in order to maximize a weighted average of the value of its shareholders' portfolios. An increase in common ownership is modeled as an increase in λ in our analysis. Notice, that $\lambda = 0$ corresponds to independently maximizing firms, whereas $\lambda = 1$ corresponds to a cartel or a full merger, respectively, i.e., maximizing industry profits.

The firms employ capital and labor as inputs. For simplicity we assume that the supplies of these two factors are iso-elastic and given by inverse supply functions $r = K^{\psi}$ and $w = L^{\beta}$, with $\psi, \beta > 0$. We assume that firms behave as price takers in the factor markets.[2]

Each firm has access to the same set of technologies combining quantities of a continuum of different tasks $x \in [0,1]$. In particular, the production function of firm j is given by

$$Y_j = \exp\left(\int_0^1 ln[y_j(x)]dx\right) \tag{3.3}$$

where $y_j(x)$ is the quantity of task x employed in production. Each task in turn is produced according to the following intermediary production function,

$$y_j(x) = \gamma_m(x)m_j(x) + \gamma_\ell(x)l_j(x) \tag{3.4}$$

in which quantities of machines $m_j(x)$ and labor $l_j(x)$ are perfect substitutes, and $\gamma_m(x)$ and $\gamma_\ell(x)$ are the productivity schedules of capital and labor over the task measure. We assume that firms can convert one unit of capital into one unit of machines.

[2]Notice that the price taking assumption in the input markets can be motivated by having a large number of identical duopolies sharing the same inputs markets and facing an aggregate demand function. If common ownership changes in the whole economy, our results derived from the analysis of a single duopoly would be the same in a set-up with a large number of duopolies.

The profit function of firm j is given by

$$\pi_j = \quad (a - Y_j - Y_{-j})Y_j - \int_0^1 \rho(x) y_j(x) dx, \tag{3.5}$$

where $\rho(x)$ is the marginal cost (price) of the intermediary good (task) produced by capital or labor. The economic price $\rho(x)$, i.e.,the marginal cost of producing a task x is given by

$$\rho(x) = \begin{cases} \frac{r}{\gamma_m(x)}, & \text{if produced with capital.} \\ \frac{w}{\gamma_l(x)}, & \text{if produced with labor.} \end{cases} \tag{3.6}$$

Moreover, we assume that $\gamma_\ell(x)/\gamma_m(x)$ is continuously differentiable and that tasks are sorted such that

$$\frac{d}{dx}\left(\frac{\gamma_\ell(x)}{\gamma_m(x)}\right) > 0. \tag{3.7}$$

This implies that labor has a comparative advantage in *higher-indexed* tasks.

3.3.1 Model's solution

Given a degree of internalization of the rivals profit, or, a degree of common ownership, $\lambda \in [0,1]$, each firm $j = 1,2$ maximizes its objective function (3.2), while taking as given the rivals choices (Cournot assumption). We seek a symmetric Nash equilibrium in pure strategies. A strategy profile of the Cournot Game is a tuple $(Y_1, Y_2) \in \mathbb{R}^2_+$. A task x is produced with capital (labor) if the marginal cost given by (3.6) of producing with capital is lower (higher) than producing this task with labor (capital). Hence, given the factor prices, the productivity schedules and the assumption in (3.7), there exists a threshold $I_j \in [0,1]$, such that all tasks $x < I_j$ are produced with capital and all tasks $x \geq I_j$ are produced with labor. In particular, I_j solves the following equation:

$$\frac{\gamma_m(I_j)}{\gamma_\ell(I_j)} = \frac{r}{w}. \tag{3.8}$$

The effective cost of producing task I_j with capital is equal to the effective cost of producing it with labor. We refer to an increase in I_j as automation, i.e., capital replacing labor in the performance of some tasks. We show in the Appendix (section B.1), that the following production function can be derived:

$$Y_j = G_j \left(\frac{K_j}{I_j}\right)^{I_j} \left(\frac{L_j}{1-I_j}\right)^{1-I_j}, \tag{3.9}$$

with,

$$G_j = \exp\left(\int_0^{I_j} \ln\left(\gamma_m(x)\right) dx + \int_{I_j}^{1} \ln\left(\gamma_\ell(x)\right) dx\right). \tag{3.10}$$

The crucial difference between (3.9) and a standard Cobb-Douglas production function is that the input shares are not exogenous, but react to changes in input prices. G_j, total factor productivity, is a function of the productivity schedules and of the degree of automation, I_j.

Since both input markets are competitive, we can use the dual problem to compute the conditional factor demands and the total cost function of each firm. Given factor prices, the degree of automation as shown above is constant and, therefore, the conditional demands only depend on the output of each firm. Notice, as well, that when the firm minimizes cost, it does not take into account its effect on factor prices and, therefore, ignores the effect of its factors demands on the profit of its rival, i.e., its common ownership incentives. Therefore, we can state the following Lemma.

Lemma 1. *The conditional demands of capital and labor are,*

$$K_j(\bar{Y}_j, r, w) = \frac{I_j}{G_j\left(\frac{w}{r}\right)^{I_j-1}} \cdot \bar{Y}_j \tag{3.11}$$

$$L_j(\bar{Y}_j, r, w) = \frac{(1-I_j)}{G_j\left(\frac{w}{r}\right)^{I_j}} \cdot \bar{Y}_j \tag{3.12}$$

Given these conditional factor demands, the cost function of the firms is,

$$C(\bar{Y}_j, r, w) = \frac{r^{I_j} w^{1-I_j}}{G_j} \cdot \bar{Y}_j. \tag{3.13}$$

Proof. See Section B.2 of the Appendix. □

As can be seen, given the constant return to scale of the production function, the total cost of the firm is linear in output and the marginal cost is constant. As explained above intuitively, for any output level, the cost minimizing degree of automation is given by (3.8). We show formally in the appendix (Section B.3) that (3.8) can be derived from the minimization of the marginal cost of the firm.

Now, we can proceed to write down the objective function (3.2) using firms' profits (3.5) and the cost function (3.13). Firm j solves the following program:

$$\max_{Y_j} \quad (a - Y_j - Y_{-j})Y_j - \frac{r^{I_j} w^{1-I_j}}{G_j} Y_j + \lambda \left\{ (a - Y_j - Y_{-j})Y_{-j} - rK_{-j} - wL_{-j} \right\},$$

subject to

$$I_j \quad \text{solves} \quad \frac{\gamma_m(I_j)}{\gamma_\ell(I_j)} = \frac{r}{w}.$$

This program has the following solution:

$$Y_j = \frac{1}{2}\left(a - (1+\lambda)Y_{-j} - \frac{r^{I_j} w^{1-I_j}}{G_j}\right) \equiv BR_j(Y_{-j}), \tag{3.14}$$

where, $BR(Y_{-j})$ is the best response of firm j given the actions of firm $-j$. By plugging expression (3.14) into the conditional factor demands (3.11) and (3.12), we obtain the solution functions of the optimal input demands $K_j(\bar{Y}_{-j}, r, w)$ and $L_j(\bar{Y}_{-j}, r, w)$. It is clear from equation (3.14) that, an increase in common ownership, λ, decreases the optimal output of the firm given the output of the rival. From there it follows that it decreases also conditional factor demands.

Nash Equilibrium of the production side

We now derive the Nash equilibrium of the production side, by solving for the fixed point of the two best-response functions. Notice that, given prices, $I_j = I$, $G_j = G$ for $j = 1, 2$. In the symmetric Nash equilibrium, $Y_j = Y_{-j}$, and we can solve for Y_j from expression (3.14) and obtain,

$$Y_j^{NE} = \frac{1}{3+\lambda}\left(a - \frac{r^I w^{1-I}}{G}\right), \tag{3.15}$$

$$K_j^{NE} = \frac{I}{G\left(\frac{w}{r}\right)^{I-1}} \cdot Y_j^{NE} \tag{3.16}$$

$$L_j^{NE} = \frac{(1-I)}{G\left(\frac{w}{r}\right)^{I}} \cdot Y_j^{NE}. \tag{3.17}$$

Definition of general equilibrium

An equilibrium is a vector of prices (w, r) and quantities (Y_j, K_j, L_j) for $j = 1, 2$, such that

1. Prices are given by the inverse supply functions

$$w = L^{\beta}, \quad r = K^{\psi}.$$

2. The firms compete à la Cournot with common ownership in the product market, i.e., for $j = 1, 2$

$$Y_j = Y^{NE}(w, r),$$
$$K_j = K^{NE}(w, r),$$
$$L_j = L^{NE}(w, r).$$

3. Markets clear, i.e., for $j = 1, 2$

$$2Y_j = Y,$$
$$2K_j = K,$$
$$2L_j = L.$$

3.4 Effect of common ownership on automation

The effect of increasing common ownership on the degree of automation is described in the following proposition:

Proposition 2. *The effect of common ownership on automation depends on the relationship between the elasticities of the inputs supply functions. In particular, we have*

$$\frac{\partial I_j}{\partial \lambda} : \begin{cases} > 0 & \textit{if} \quad \psi - \beta > 0, \\ = 0 & \textit{if} \quad \psi - \beta = 0, \\ < 0 & \textit{if} \quad \psi - \beta < 0. \end{cases} \tag{3.18}$$

Proof. We first consider the effect of increasing common ownership on factors demand, given prices. As already explained, it is easy to see from equations (3.15), (3.16) and, (3.17), that an increase in common ownership decreases the demand for inputs. Importantly, however, common ownership does not change the relative demand curve. By taking the ratio of (3.16) and (3.17) we obtain,

$$\frac{K_j}{L_j} = \frac{I\left(\frac{r}{w}\right)}{1 - I\left(\frac{r}{w}\right)} \frac{w}{r} \tag{3.19}$$

where we made explicit that I, the degree of automation, depends on prices. The interpretation of this is very straightforward. The degree of common ownership does not affect the optimal allocation of inputs given factor prices. In other words, common ownership does not change the cost-minimization problem of the firm. As common ownership increases, the firms decrease the demand for inputs, keeping constant the relative demand. To understand the effect of common ownership on the input price ratio in equilibrium, we need to consider the relative supply curve. We take the ratio of the inverse supply functions $r = K^{\psi}$ and $w = L^{\beta}$ and we obtain,[3]

$$\frac{r}{w} = \frac{K^{\psi}}{L^{\beta}} = \left(\frac{K}{L}\right)^{\psi} L^{\psi-\beta}. \tag{3.20}$$

Given symmetry, the aggregate relative demand curve is equal to the relative demand curve of firm j.[4] The effect on the equilibrium price ratio depends on the relationship between the elasticities of the supply functions, ψ and β. In particular, we have,

$$\frac{\partial\left(r/w\right)}{\partial\lambda} : \begin{cases} < 0 & \text{if} \quad \psi - \beta > 0, \\ = 0 & \text{if} \quad \psi - \beta = 0, \\ > 0 & \text{if} \quad \psi - \beta < 0. \end{cases} \tag{3.21}$$

As the automation decision depends only on the price ratio (see (3.8)), and because of the assumption (3.7), we obtain the result in (3.18) for the effect of an increase in common ownership on automation. □

A graphical representation of the effect of common ownership on equilibrium is presented in Figure 3.1. We plot the curve for the case of $\psi \in (0, 1)$

[3]Or, alternatively,

$$\frac{r}{w} = \left(\frac{K}{L}\right)^{\beta} K^{\psi-\beta}.$$

[4]Formally,

$$\frac{K^d}{L^d} = \frac{K_1^d + K_2^d}{L_1^d + L_2^d} = \frac{2K_1^d}{2L_1^d} = \frac{K_1^d}{L_1^d}.$$

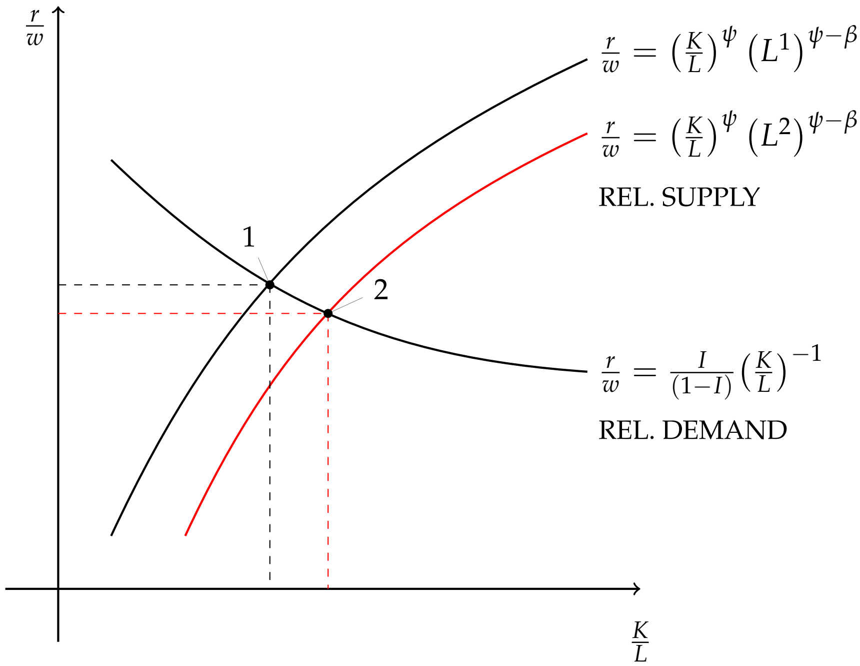

FIGURE 3.1: Graphical representation of the effect of an *increase* in common ownership on equilibrium. The curves are drawn assuming that $\psi \in (0,1)$ and $\psi > \beta$. The two equilibria depicted are characterized by a different value of common ownership with $\lambda^1 < \lambda^2$. As explained in the text, a higher value of common ownership implies a lower equilibrium value of production and input use, i.e, $L^2 < L^1$.

and $\psi - \beta > 0$. By looking at the Figure, it is clear that an increase in common ownership, somehow counter-intuitively, shifts the relative *supply* curve.

To sum up, an increase in common ownership decreases the demand for production inputs while keeping the relative demand unchanged. Therefore, the percentage change of the demanded input is the same for capital and labor. If the elasticities of the two supply functions are the same, the percentage decreases of the two prices are also equal and the price ratio is not affected by an increase in common ownership. Consequently, the degree of automation is also unaffected by common ownership. On the contrary, if one price decreases proportionally more than the other, the price ratio changes with common ownership. Our model predicts that an increase in common ownership increases automation if the elasticity of the inverse supply function of capital is greater than the elasticity of the inverse supply function of labor. Equivalently, if the elasticity of the supply function of capital is lower than the elasticity of the supply function of labor, the incentives to automate increases with rising common ownership.

3.5 Conclusion

We study how increasing common ownership, a rising phenomenon in many countries, affects automation technology adoption. We develop a simple Cournot duopoly model with overlapping ownership of firms and endogenous automation decision. We find that the effect only depends on the relationship between the elasticities of the supply functions of capital and labor. The interpretation of this result is straightforward. Increasing common ownership decreases the demands of capital and labor but does not affect the relative demand curve. The elasticities of the inverse supply functions, therefore, determine which price decreases the most and the effect on the price ratio in equilibrium. The effect on the equilibrium price ratio determines the effect of common ownership on automation.

Bibliography

Acemoglu, Daron and David Autor (2011). "Skills, tasks and technologies: Implications for employment and earnings". In: *Handbook of labor economics*. Vol. 4. Elsevier, pp. 1043–1171.

Acemoglu, Daron, Claire LeLarge, and Pascual Restrepo (2020). *Competing with Robots: Firm-Level Evidence from France*. Tech. rep. National Bureau of Economic Research.

Acemoglu, Daron and Pascual Restrepo (2017). "Robots and jobs: Evidence from US labor markets". In:

— (2018). "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment". In: *American Economic Review* 108.6, pp. 1488–1542.

— (2019). "Automation and new tasks: how technology displaces and reinstates labor". In: *Journal of Economic Perspectives* 33.2, pp. 3–30.

— (2020). "Robots and jobs: Evidence from US labor markets". In: *Journal of Political Economy* 128.6, pp. 2188–2244.

Aghion, Philippe, John Van Reenen, and Luigi Zingales (2013). "Innovation and institutional ownership". In: *American economic review* 103.1, pp. 277–304.

Aguiar, Mark and Mark Bils (2015). "Has consumption inequality mirrored income inequality?" In: *American Economic Review* 105.9, pp. 2725–56.

Ahmad, Mumtaz, John Fernald, and Hashmat Khan (2019). *Returns to Scale in US Production, Redux*. Tech. rep.

Aiyagari, S Rao (1994). "Uninsured idiosyncratic risk and aggregate saving". In: *The Quarterly Journal of Economics* 109.3, pp. 659–684.

Anelli, Massimo, Italo Colantone, and Piero Stanig (2020). "We Were the Robots: Automation and Voting Behavior in Western Europe". In:

Anton, Miguel, José Azar, Mireia Gine, and Luca Xianran Lin (2020). "Beyond the Target: M&A Decisions and Rival Ownership". In: *Available at SSRN 3226390*.

Anton, Miguel, Florian Ederer, Mireia Gine, and Martin C Schmalz (2018). "Innovation: the bright side of common ownership?" In: *Available at SSRN 3099578*.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn (2016). “The risk of automation for jobs in OECD countries: A comparative analysis”. In: *OECD Social, Employment, and Migration Working Papers* 189, 0_1.

Attanasio, Orazio, Erich Battistin, and Hidehiko Ichimura (2004). *What really happened to consumption inequality in the US?* Tech. rep. National Bureau of Economic Research.

Attanasio, Orazio and Luigi Pistaferri (2014). “Consumption inequality over the last half century: some evidence using the new PSID consumption measure”. In: *American Economic Review* 104.5, pp. 122–26.

Attanasio, Orazio P and Luigi Pistaferri (2016). “Consumption inequality”. In: *Journal of Economic Perspectives* 30.2, pp. 3–28.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen (2020). “The fall of the labor share and the rise of superstar firms”. In: *The Quarterly Journal of Economics* 135.2, pp. 645–709.

Azar, José, Sahil Raina, and Martin C Schmalz (2019). “Ultimate ownership and bank competition”. In: *Available at SSRN 2710252*.

Azar, José, Martin C Schmalz, and Isabel Tecu (2018). “Anticompetitive effects of common ownership”. In: *The Journal of Finance* 73.4, pp. 1513–1565.

Azar, José and Xavier Vives (2019). “Common ownership and the secular stagnation hypothesis”. In: *AEA Papers and Proceedings*. Vol. 109, pp. 322–26.

— (2020). “General Equilibrium Oligopoly and Ownership Structure”. In:

Backus, Matthew, Christopher Conlon, and Michael Sinkinson (2019). *Common ownership in america: 1980-2017*. Tech. rep. National Bureau of Economic Research.

Baker, Jonathan B (2015). “Overlapping financial investor ownership, market power, and antitrust enforcement: My qualified agreement with Professor Elhauge”. In: *Harv. L. Rev. F.* 129, p. 212.

Ben-David, Itzhak, Francesco Franzoni, Rabih Moussawi, and John Sedunov (2016). *The granular nature of large institutional investors*. Tech. rep. National Bureau of Economic Research.

Berg, Andrew, Edward F Buffie, and Luis-Felipe Zanna (2018). “Should we fear the robot revolution? (The correct answer is yes)”. In: *Journal of Monetary Economics* 97, pp. 117–148.

Bergholt, Drago, Francesco Furlanetto, and Nicolò Maffei Faccioli (2020). “The decline of the labor share: New empirical evidence”. In: *American Economic Journal: Macroeconomics* forthcoming.

Bewley, Truman (1986). “Stationary monetary equilibrium with a continuum of independently fluctuating consumers”. In: *Contributions to mathematical economics in honor of Gérard Debreu* 79.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen (2013). “Identifying technology spillovers and product market rivalry”. In: *Econometrica* 81.4, pp. 1347–1393.

Brooks, Chris, Zhong Chen, and Yeqin Zeng (2018). “Institutional cross-ownership and corporate strategy: The case of mergers and acquisitions”. In: *Journal of Corporate Finance* 48, pp. 187–216.

Cords, Dario and Klaus Prettner (2019). *Technological unemployment revisited: Automation in a search and matching framework*. Tech. rep. Global Labor Organization (GLO) Discussion Paper, No. 308.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner (2021). “The Adjustment of Labor Markets to Robots”. In: *Journal of the European Economic Association* forthcoming.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger (2020). “The rise of market power and the macroeconomic implications”. In: *The Quarterly Journal of Economics* 135.2, pp. 561–644.

Dolado, Juan, Florentino Felgueroso, and Juan F Jimeno (2020). “The Spanish Labour Market at the Crossroads: Covid-19 meets the Megatrends”. In:

Dolado, Juan J, Gergö Motyovszki, and Evi Pappa (2020). “Monetary Policy and Inequality under Labor Market Frictions and Capital-Skill Complementarity”. In: *American Economic Journal: Macroeconomics* forthcoming.

Eden, Maya and Paul Gaggl (2018). “On the Welfare Implications of Automation”. In: *Review of Economic Dynamics* 29, pp. 15–43.

Frey, Carl Benedikt and Michael A Osborne (2017). “The future of employment: how susceptible are jobs to computerisation?” In: *Technological Forecasting and Social Change* 114, pp. 254–280.

Graetz, Georg and Guy Michaels (2018). “Robots at work”. In: *Review of Economics and Statistics* 100.5, pp. 753–768.

Grigoli, Francesco, Zsoka Koczan, and Petia Topalova (2020). “Automation and Labor Force Participation in Advanced Economies: Macro and Micro Evidence”. In: *European Economic Review*, p. 103443.

Guerreiro, Joao, Sergio Rebelo, and Pedro Teles (2017). *Should robots be taxed?* Tech. rep. National Bureau of Economic Research.

Guvenen, Fatih (2009). “An empirical investigation of labor income processes”. In: *Review of Economic dynamics* 12.1, pp. 58–79.

Hansen, Lars Peter and Kenneth J Singleton (1983). "Stochastic consumption, risk aversion, and the temporal behavior of asset returns". In: *Journal of Political Economy* 91, pp. 249–265.

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L Violante (2010). "Unequal we stand: An empirical analysis of economic inequality in the United States, 1967–2006". In: *Review of Economic dynamics* 13.1, pp. 15–51.

Heckman, James J, Lance Lochner, and Christopher Taber (1998). "Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents". In: *Review of economic dynamics* 1.1, pp. 1–58.

Hellerstein, Judith K, David Neumark, and Kenneth R Troske (1999). "Wages, productivity, and worker characteristics: Evidence from plant-level production functions and wage equations". In: *Journal of labor economics* 17.3, pp. 409–446.

Hémous, David and Morten Olsen (2014). "DP10244 The Rise of the Machines: Automation, Horizontal Innovation and Income Inequality". In:

Hubmer, Joachim, Per Krusell, and Anthony A Smith Jr (2016). *The historical evolution of the wealth distribution: A quantitative-theoretic investigation*. Tech. rep. National Bureau of Economic Research.

Huggett, Mark (1993). "The risk-free rate in heterogeneous-agent incomplete-insurance economies". In: *Journal of economic Dynamics and Control* 17.5-6, pp. 953–969.

Iftikhar, Zainab and Anna Zaharieva (2019). "General equilibrium effects of immigration in Germany: Search and matching approach". In: *Review of Economic Dynamics* 31, pp. 245–276.

Jaimovich, Nir, Itay Saporta-Eksten, Henry E Siu, and Yaniv Yedid-Levi (2020). *The macroeconomics of automation: Data, theory, and policy analysis*. Tech. rep. National Bureau of Economic Research.

Jordà, Òscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M Taylor (2019). "The rate of return on everything, 1870–2015". In: *The Quarterly Journal of Economics* 134.3, pp. 1225–1298.

Kaymak, Barış and Markus Poschke (2016). "The evolution of wealth inequality over half a century: The role of taxes, transfers and technology". In: *Journal of Monetary Economics* 77, pp. 1–25.

Kneip, Alois, Monika Merz, and Lidia Storjohann (2020). "Aggregation and labor supply elasticities". In: *Journal of the European Economic Association* 18.5, pp. 2315–2358.

Knoblach, Michael, Martin Roessler, and Patrick Zwerschke (2020). "The elasticity of substitution between capital and labour in the US economy: A meta-regression analysis". In: *Oxford Bulletin of Economics and Statistics* 82.1, pp. 62–82.

Leduc, Sylvain and Zheng Liu (2020a). "Can Pandemic-Induced Job Uncertainty Stimulate Automation?" In: Federal Reserve Bank of San Francisco.

— (2020b). "Robots or Workers? A Macro Analysis of Automation and Labor Markets". In: Federal Reserve Bank of San Francisco.

Lerch, Benjamin (2020). "Robots and Nonparticipation in the US: Where Have All the Displaced Workers Gone?" In: *Available at SSRN 3650905*.

López, Ángel L and Xavier Vives (2019). "Overlapping ownership, R&D spillovers, and antitrust policy". In: *Journal of Political Economy* 127.5, pp. 2394–2437.

Macho-Stadler, Ines and Thierry Verdier (1991). "Strategic managerial incentives and cross ownership structure: a note". In: *Journal of Economics* 53.3, pp. 285–297.

Maioli, Sara (2004). "A Joint Estimation of Markups and Returns to Scale in 30 French Industries: A Structural Approach". In:

Moll, Benjamin, Lukasz Rachel, and Pascual Restrepo (2019). "Uneven growth: automation's impact on income and wealth inequality". In: *Manuscript, Princeton University*.

Oberfield, Ezra and Devesh Raval (2020). "Micro data and macro technology". In: *Econometrica* forthcoming.

O'Brien, Daniel P and Steven C Salop (1999). "Competitive effects of partial ownership: Financial interest and corporate control". In: *Antitrust LJ* 67, p. 559.

Posner, Eric A, Fiona M Scott Morgan, and E Glen Weyl (2016). "A proposal to limit the anticompetitive power of institutional investors". In: *Antitrust LJ* 81, p. 669.

Priftis, Romanos and Kirill Shakhnov (2020). "Sectoral Reallocation: Long-Run Trends and Short-Run Fluctuations of the Last 150 Years". In: *mimeo*.

Ravn, Morten O (2008). "The Consumption-Tightness Puzzle". In: *NBER International Seminar on Macroeconomics 2006*. University of Chicago Press, pp. 9–63.

Sachs, Jeffrey D, Seth G Benzell, and Guillermo LaGarda (2019). "Robots: Curse or blessing? A basic framework". In: *mimeo*.

Seldeslachts, Jo, Melissa Newham, and Albert Banal-Estanol (2017). "Changes in common ownership of German companies". In: *DIW Economic Bulletin* 7.30, pp. 303–311.

Zeira, Joseph (1998). "Workers, machines, and economic growth". In: *The Quarterly Journal of Economics* 113.4, pp. 1091–1117.

Appendix A

Appendix: Chapter 2

A.1 Proof of Proposition 1

Proof. From the maximization problem of the household we have,

$$\Phi l_t^{-\varphi} = \lambda_{n^{M_t}} \psi_t^{hM} s_t + \lambda_n s_t \psi_t^{hS} (1 - s_t) + \lambda_{ct} \bar{b}_t, \tag{A.1}$$

and

$$\lambda_{n^{M_t}} \psi_t^{hM} = \lambda_{n^{S_t}} \psi_t^{hS}. \tag{A.2}$$

We can substitute (A.2) into (A.1) and obtain,

$$\Phi l_t^{-\varphi} = \lambda_{n^{S_t}} \psi_t^{hM} + \lambda_{ct} \bar{b}_t,$$

or alternatively we can get,

$$\Phi l_t^{-\varphi} = \lambda_{n^{S_t}} \psi_t^{hS} + \lambda_{ct} \bar{b}_t,$$

which states that the marginal utility of leisure is equal to the value of being unemployed. The latter in turn is equal to the utility value of the unemployment benefit plus the probability of finding a job times the value of being employed. We invert these equations and obtain,

$$\lambda_{n^{M_t}} = \frac{\Phi l_t^{-\varphi} - \lambda_{ct} \bar{b}_t}{\psi_t^{hM}},$$

and

$$\lambda_{n^{S_t}} = \frac{\Phi l_t^{-\varphi} - \lambda_{ct} \bar{b}_t}{\psi_t^{hS}}.$$

The values of an additional unit of employment in the two sectors are,

$$V_{n^{M_t}}^h = \lambda_{ct} w_t^M - \Phi l_t^{-\varphi} + \left(1 - \sigma^M\right) \lambda_{n^{M_t}},$$

and

$$V^h_{n^{S_t}} = \lambda_{ct} w^S_t - \Phi l_t^{-\varphi} + \left(1 - \sigma^S\right) \lambda_n s_t.$$

The Lagrange multipliers λ_{n^M} and λ_{n^S} are equal to,

$$\lambda_{n^{M_t}} = \beta E_t \left[\lambda_{c,t+1} w^M_{t+1} - \Phi l_{t+1}^{-\varphi} + \lambda_{n^{M_{t+1}}} (1 - \sigma^M)\right],$$

and

$$\lambda_{n^{S_t}} = \beta E_t \left[\lambda_{c,t+1} w^S_{t+1} - \Phi l_{t+1}^{-\varphi} + \lambda_n s_{t+1} (1 - \sigma^S)\right].$$

Therefore, we can write,

$$\lambda_{n^{S_t}} = \beta E_t \left[V^h_{n^{S_{t+1}}}\right], \tag{A.3}$$

and

$$\lambda_{n^{M_t}} = \beta E_t \left[V^h_{n^{M_{t+1}}}\right]. \tag{A.4}$$

Consider now the problems of the two representative firms where the first-order conditions with respect to vacancies are given by,

$$\frac{\kappa^M}{\psi_t^{fM}} = E_t \Lambda_{t,t+1} \left[p^M_{t+1} (1 - \zeta) \left(\frac{M_{t+1}}{n^M_{t+1}}\right)^{\frac{1}{\alpha}} - w^M_{t+1} + \frac{\left(1 - \sigma^M\right) \kappa^M}{\psi^{fM}_{t+1}}\right],$$

and

$$\frac{\kappa^S}{\psi_t^{fS}} = E_t \Lambda_{t,t+1} \left[p^S_{t+1} b \frac{S_{t+1}}{n^S_{t+1}} - w^S_{t+1} + \frac{\left(1 - \sigma^S\right) \kappa^S}{\psi^{fS}_{t+1}}\right].$$

The marginal value of an extra unit of employment in period t for each sector is,

$$V^f_{n^M t} = p^M_t (1 - \zeta) \left(\frac{M_t}{n^M_t}\right)^{\frac{1}{\alpha}} - w^M_t + \frac{\left(1 - \sigma^M\right) \kappa^M}{\psi^{fM}_t},$$

and

$$V^f_{n^S t} = p^S_t b \frac{S_t}{n^S_t} - w^S_t + \frac{\left(1 - \sigma^S\right) \kappa^S}{\psi^{fS}_t}.$$

Therefore, we can write,

$$\frac{\kappa^M}{\psi_t^{fM}} = E_t \Lambda_{t,t+1} \left[V^f_{n^M t+1}\right], \tag{A.5}$$

and

$$\frac{\kappa^S}{\psi_t^{fS}} = E_t \Lambda_{t,t+1} \left[V^f_{n^S t+1}\right].$$

Recall that the first-order conditions of the wage bargaining problems are,

$$\vartheta^M V^h_{n^M t} = \left(1 - \vartheta^M\right) \lambda_{ct} V^f_{n^M t}, \tag{A.6}$$

and

$$\vartheta^S V^h_{n^S t} = \left(1 - \vartheta^S\right) \lambda_{ct} V^f_{n^S t}.$$

By evaluating equation (A.6) for the next period, multiplying by $\frac{\beta}{\lambda_{c,t}}$, and taking expectations we obtain,

$$\frac{\vartheta^M}{\lambda_{c,t}} \beta E_t \left[V^h_{n^M t+1}\right] = \left(1 - \vartheta^M\right) E_t \Lambda_{t,t+1} \left[V^f_{n^M t+1}\right].$$

Substituting (A.4) and (A.5) we get,

$$\frac{\vartheta^M}{\lambda_{c,t}} \frac{\left(\Phi l_t^{-\varphi} - \lambda_{ct} \bar{b}_t\right)}{\psi_t^{hM}} = \left(1 - \vartheta^M\right) \frac{\kappa^M}{\psi_t^{fM}},$$

and, after rearranging terms, we obtain,

$$\theta_t^M = \frac{\vartheta^M}{1 - \vartheta^M} \frac{\left(\Phi l_t^{-\varphi} - \lambda_{ct} \bar{b}_t\right)}{\kappa^M}.$$

Similarly for the service sector, we have,

$$\theta_t^S = \frac{\vartheta^S}{1 - \vartheta^S} \frac{\left(\Phi l_t^{-\varphi} - \lambda_{ct} \bar{b}_t\right)}{\kappa^S}.$$

These relations are similar to the the linear relationship between labor market tightness and the marginal utility of consumption derived by Ravn, 2008 in a one-sector search and matching model with endogenous participation. By taking the ratio of tightness in the two sectors, we obtain the relationship of Proposition 1.

$$\frac{\theta_t^M}{\theta_t^S} = \frac{\frac{\vartheta^M}{1-\vartheta^M}}{\frac{\vartheta_S}{1-\vartheta_S}} \cdot \frac{\kappa^S}{\kappa^M}.$$

□

Appendix B

Appendix: Chapter 3

B.1 Derivation of of the production function (3.9)

The Lagrangian of the cost minimization problem given the production function (3.3) and the task-specific production functions (3.4) as well as the optimal threshold I given in (3.8) can be written as

$$\begin{aligned}\mathcal{L}(\{m(x)\}_{x=0}^{I},\{l(x)\}_{x=I}^{1},\mu) \\ &= \int_0^I rm(x)dx + \int_I^1 wl(x)dx \\ &\quad + \mu\left\{\bar{Y} - \exp\left(\int_0^I \ln[\gamma_m(x)m(x)]dx\right)\exp\left(\int_I^1 \ln[\gamma_l(x)l(x)dx]\right)\right\},\end{aligned} \tag{B.1}$$

where $\bar{Y}$ is any fixed production level and μ is the Lagrange multiplier. The program (B.1) yields the following first-order conditions:

$$m(x) = \frac{\mu\bar{Y}}{r}, \qquad \forall\, x < I, \tag{B.2}$$

$$l(x) = \frac{\mu\bar{Y}}{w}, \qquad \forall\, x \geq I, \tag{B.3}$$

$$\bar{Y} = \exp\left(\int_0^I \ln[\gamma_m(x)m(x)]dx\right)\exp\left(\int_I^1 \ln[\gamma_l(x)l(x)dx]\right). \tag{B.4}$$

Notice that within each set of tasks $[0, I)$ and $[I, 1]$ the same amount of labor and machines is employed. Assuming that firms can convert one unit of capital into one unit of machines, the total demands of capital and labor by firm j in order to produce $\bar{Y}$ are given by

$$K_j = \int_0^{I_j} m_j(x)dx = \frac{\mu\bar{Y}}{r} I_j, \tag{B.5}$$

$$L_j = \int_{I_j}^0 l_j(x)dx = \frac{\mu\bar{Y}}{w}(1 - I_j). \tag{B.6}$$

Using (B.3-B.6) and defining

$$\Gamma_{m,j} = \int_0^{I_j} \ln \gamma_m(x)dx$$
$$\Gamma_{l,j} = \int_{I_j}^1 \ln \gamma_l(x)dx,$$

we can rewrite firm j's production function as

$$\begin{aligned}
\ln \bar{Y}_j &= \int_0^{I_j} \ln[\gamma_m(x)m_j(x)]dx + \int_{I_j}^1 \ln[\gamma_l(x)l_j(x)]dx \\
&= \Gamma_{m,j} + \Gamma_{l,j} + \int_0^{I_j} \ln[m_j(x)]dx + \int_{I_j}^1 \ln[l_j(x)]dx \\
&= \Gamma_{m,j} + \Gamma_{l,j} + \int_0^{I_j} dx \ln\left[\frac{\mu\bar{Y}_j}{r}\right] + \int_{I_j}^1 dx \ln\left[\frac{\mu\bar{Y}_j}{w}\right] \\
&= \Gamma_{m,j} + \Gamma_{l,j} + I_j \ln\left[\frac{\mu\bar{Y}_j}{r}\right] + (1 - I_j) \ln\left[\frac{\mu\bar{Y}_j}{w}\right] \\
&= \Gamma_{m,j} + \Gamma_{l,j} + \ln\left[\left(\frac{K_j}{I_j}\right)^{I_j}\right] + \ln\left[\left(\frac{L_j}{1 - I_j}\right)^{1-I_j}\right]
\end{aligned}$$

Therefore, firm j's output is given by

$$Y_j = G_j \left(\frac{K_j}{I_j}\right)^{I_j} \left(\frac{L_j}{1 - I_j}\right)^{1-I_j}, \tag{B.7}$$

where $G = \exp[\Gamma_{m,j} + \Gamma_{l,j}]$.

B.2 Derivation of conditional factor demand and cost function of the firms

We omit the sub-index j for simplicity. Given $\bar{Y}$, the cost minimization of the firm is,

$$\min_{\{K,L\}} \quad rK + wL + \mu\left[\bar{Y} - G\left(\frac{K}{L}\right)^{I}\left(\frac{L}{1-I}\right)^{1-I}\right].$$

The first order condition with respect to K is,

$$r = \mu\bar{Y}\frac{I}{K},$$

and, with respect to L is

$$w = \mu\bar{Y}\frac{1-I}{L}.$$

To obtain the conditional relative demand, we take the ratio of the two previous expressions,

$$\frac{r}{w} = \frac{I}{1-I}\frac{L}{K}.$$

With this, we can express the demand for capital with respect to the demand for labor. By plugging this expression in the production function we obtain,

$$\bar{Y} = G\left(\frac{w}{r}\right)^{I}\frac{L}{1-I}.$$

Solving for L, gives us the conditional factor demand for labor,

$$L(\bar{Y}, r, w) = \frac{(1-I)}{G\left(\frac{w}{r}\right)^{I}} \cdot \bar{Y}.$$

By applying similar steps, we derive the conditional factor demand for capital,

$$K(\bar{Y}, r, w) = \frac{I}{G\left(\frac{w}{r}\right)^{I-1}} \cdot \bar{Y}.$$

By using the expressions for the conditional factor demands, we obtain the expression for the cost function,

$$C(\bar{Y}, r, w) = r \cdot K(\bar{Y}, r, w) + w \cdot L(\bar{Y}, r, w) = \frac{r^{I}w^{1-I}}{G} \cdot \bar{Y}.$$

B.3 Derivation of expression (3.8) from the marginal cost function

In this section, we show that by minimizing the marginal cost function (3.13) with respect to I, the degree of automation, we obtain the expression in (3.8).

$$
\begin{aligned}
&\frac{\partial}{\partial I}\frac{r^I w^{1-I}}{G(I)} = 0,\\
&\frac{r^I \ln(r) w^{1-I}}{G(I)} - \frac{r^I w^{1-I}\ln(w)}{G(I)} - \frac{r^I w^{1-I}}{G(I)}\left[\ln\left(\gamma_m(I)\right) - \ln\left(\gamma_\ell(I)\right)\right] = 0,\\
&\frac{r^I w^{1-I}}{G(I)}\left[\ln(r) - \ln(w) - \ln\left(\gamma_m(I)\right) + \ln\left(\gamma_\ell(I)\right)\right] = 0.
\end{aligned}
$$

From the last expression, we see that the derivative is equal to zero if,

$$
\begin{aligned}
\ln\left(\frac{r}{w}\right) &= \ln\left(\frac{\gamma_m(I)}{\gamma_\ell(I)}\right),\\
\frac{r}{w} &= \frac{\gamma_m(I)}{\gamma_\ell(I)}.
\end{aligned}
$$