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Human Capital and Job Polarization

Evidences from European countries

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Abstract

Over the past decades, advanced economies underwent large changes of their employment structure. Job polarization has been linked mainly to three different causes: globalization, routinization and structural change. In this Master's thesis, I investigate the dynamics behind job polarization, human capital and structural change. Therefore, I test the model of Bárány and Siegel (2018), a multi-sector growth model, using data from major European countries. Structural change is, indeed, behind employment polarization. However, diverse human capital could determine different outcomes on productivity. Therefore, I explain how human capital matters, starting from the intuitions of the model of human capital Nelson-Phelps (1965) and Baumol (1967). This Master's thesis offers a novel theoretical explanation on the interaction between job polarization, structural change and productivity slowdown, with a focus on the fundamental role of human capital.

Keywords: Job Polarization; Structural Change; Unbalanced Growth; Human Capital; Multi-Sector Growth Model

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1 Introduction

The *Future of Work*, as the OECD has defined it in a series of reports, remains rather uncertain. The transformation and the obsolescence of known occupations are generating a growing fear regarding the impact of technological advancement: is there a concrete possibility for experiencing *technological unemployment*? Are we going towards a so-called *robocalypse* scenario (Author and Salomons, 2017)? From David Ricardo to John Maynard Keynes, there remains a long-standing question in economics: are machines going to substitute humans? What is the impact of technical change on the employment structure? What is the impact on wage levels?

Academic literature offers us some answers. The introduction of modern technologies generates a modification of the structure of the economy: a structural change (Acemoglu, 2009). Genuine structural change refers to a permanent and irreversible change of the composition of production, employment and consumption structures (Pasinetti, 1993). For instance, from the mid-17th century the agricultural revolution radically changed Western economies: in the United States, the share of employment in agriculture has fallen from 90% to less than 5% (Acemoglu, 2009). Then, since the industrialization of the Western economies in the late 18th and early 19th centuries, the manufacturing sector of these economies has maintained the greater share in total employment. Later on, during the time of globalization, the employment share majority has shifted again from manufacturing to services, a phenomenon defined *de-industrialization*. At present, over 70% of laborers work in service industries in Western economies (Acemoglu, 2009). Nonetheless, this development path has not only been observed in developed countries, but it is rather recognized in the vast majority of the World economies. China has experienced an increase of its employment in industry as percentage of total employment from 21.5% in 1991 to 28.62% in 2018 (ILOSTAT Database). Even more strikingly, Vietnamese share of employment in industry has peaked at 25.8% in 2018, starting from a modest 12.3% in 1991 (ILOSTAT Database). These trends are present even when we look at consumption shares for services, agricultural and manufactured goods (Pasinetti, 1993; Acemoglu, 2009).

Nowadays, the introduction of advanced robots, artificial intelligence and other "brilliant" technologies (Brynjolfsson and McAfee, 2014) may determine a further shift to new sectors and novel products.

1.1 Structural change and unbalanced growth

Structural change refers to the shift of employment and production between different sectors along the development path: from agriculture to manufacturing, and then from manufacturing to services (Acemoglu, 2009). The reason for these shifts is traceable in inter-sectoral productivity differentials, also known as unbalanced growth (Baumol, 1957).

Different sectors grow at diverse rates owing to different rates of technological progress or technology adoption (Acemoglu, 2009). For instance, manufacturing has a higher capability of adapting robots to its production process relative to accommodation and food services. This is one of the reasons why manufacturing exhibits higher productivity growth rates than services. In turn, improved productivity in some sectors leads to the relocation of workers towards sectors with lower productivity, as Goos, Manning and Salomons (2010) have empirically demonstrated. Therefore, unbalanced growth is accompanied by a high inter-sector mobility of labor (Pasinetti, 1993).

This phenomenon is caused by a demand-side and a supply-side effect and it is described as follows. On one hand, improved productivity lowers product prices, generating a demand-side effect. Indeed, once demand for these cheaper products becomes saturated, individuals would start to consume their income in other items. This is known as Engel's law: the structure of consumption always varies as real income changes (Pasinetti, 1993). Acemoglu (2009) has described it as "the desires of the consumers to change the composition of their consumption as they become richer". Originally, Engel's law has been applied only to primary needs, like food products. However, Pasinetti (1993) pointed out that "empirical studies have shown that the proportion of any individual's expenditure devoted to any consumption good is never constant as personal income increases" (Pasinetti, 1993). Consumer's demand always reach a point of saturation. At this point, increases in real income generates a higher consumption of other items: for instance, from agricultural products to manufacturing products.

Further, the hypothesis of Baumol (1967) - defined as unbalanced growth - is behind the supply-side effect (Acemoglu, 2009). For the sake of simplicity, we consider an economy with two sectors with a sector with high productivity and a sector with constant productivity. If the relative outputs of the two sectors are maintained, because, for instance, demand for services is sufficiently income elastic - as highlighted by the Engel's law -, Baumol (1967) expressed the following proposition: "in the unbalanced productivity model, if the ratio of the outputs of the two sectors is held constant, more and more of the total labor force must be transferred to the "non-progressive" sector and the amount of labor in the other sector will tend to approach zero". Indeed, since the demand-side effect generates an increase in the demand of both sectors, inevitably, the employment of sector 2 needs to expand if it can not increase its productivity. This causes structural change and, therefore, a change in the employment structure, with a higher inter-sectoral mobility of labor.

More recently, Bessen (2018) highlights how demand plays a pivotal role in determining employment shifts. Following the process of structural change, once the demand is saturated - as in Pasinetti (1993) - and individuals start to consume other products (and services), employment rapidly decreases. Therefore, in the long-run, employment follows an inverted-U pattern. Bessen (2018) has demonstrated how production employment in textile, primary iron and motor vehicle industries followed exactly this pattern over the period 1800-2010. Pasinetti (1993) emphasizes that "the present structural dynamics scheme brings to the fore one of the most alarming phenomena of modern industrial systems: the inevitable decline of employment in certain production sectors, as a result of the process of economic development". Therefore, structural change may have adverse outcomes. Indeed, there are two main issues to highlight: skills and wages.

1.2 Skills and skill-biased technical change

Technical change transforms - or replaces - tasks performed by workers in the production process of goods and services (Autor, 2010; Acemoglu and Autor, 2010). For instance, cheaper computers have caused a marked decline of clerks, technicians, bookkeepers, salespersons and other white-collar workers. From 1996 to 2015, in the United States, the share of the workforce employed in white-collar jobs declined from 25.5% to 21% - a 4.5 percentage points decline, or 7 million jobs (Restrepo, 2018). In fact, technical change transforms the labor market through altering the demand and supply of specific skills required to perform specific tasks. Workers with marketable skills face favorable conditions, while workers with non-marketable skills suffer from low employment levels and stagnant wages, facing an increasing risk of structural unemployment (Restrepo, 2018). Workers equipped with marketable skills obtain a *skill premium*: a significant wage increase given the acquisition of these skills. In the last decades, an extensive literature has evidenced how skill premium did not decrease even after the marked increase of graduate workers in the labor market. This phenomenon is the so-called skill-biased technical change. Indeed, technical change required production to employ a higher share of skilled workers and, therefore, even if the workforce experienced a significant increase of these workers, there have not been any substantial changes of the skill premium and, therefore, in wages (Acemoglu and Autor, 2010; Goldin and Katz, 2007).

1.3 Wages and job polarization

Wages tend to remain stagnant among those workers without marketable skills and those working in a sector with high productivity. The inter-sectoral mobility of labor is necessary when productivity differentials are high: workers are relocated from sectors with high productivity to sectors with low productivity. This relocation is possible only if the stagnant sector offers a higher relative wage. Autor and Salomons (2010) show empirically that employment shrinks in the most productive sector of the economy, but the effect is completely offset by the employment growth of lagging sectors. As theoretically predicted, this relocation is accompanied by a change of the wage structure. Indeed, diverse authors have documented how advanced economies experienced a phenomenon of employment and wage polarization during the last decades (Goos and Manning, 2003;

Goos, Manning and Salomons, 2010; Bárány and Siegel, 2018). Job polarization is a general wage and employment growth stagnation for middle-skilled and middle-paid jobs and in the middle of the distribution of earnings. As Acemoglu and Autor (2010) define it, job polarization leads to "broad-based increases in employment in high skill and low skill occupations relative to middle-skilled occupations".

Table 1: Initial Shares of Hours Worked and Percentage Changes over 1993-2010 (by Country) from Goos et al. (2014)

Country	Four lowest-paying occupations		Nine middling occupations		Eight highest-paying occupations	
	Employment share in 1993 (in percent)	Percentage point change 1993-2010	Employment share in 1993 (in percent)	Percentage point change 1993-2010	Employment share in 1993 (in percent)	Percentage point change 1993-2010
France	19.92	4.19	46.69	-8.60	33.39	4.41
Germany	20.71	2.37	48.03	-6.74	31.26	4.37
Italy	27.01	6.06	51.04	-10.59	21.94	4.53
United Kingdom	16.88	4.17	43.64	-10.94	39.49	6.77

This phenomenon has already been documented both in the U.S. and in Europe, as Table 1 (Goos et al., 2014) shows for four different European countries. Moreover, Figure 1 shows that European countries have experienced job polarization even in the last decade (2008-2018). As highlighted by Autor and Dorn (2013) and Acemoglu and Autor (2010), canonical models do not predict well job polarization and there is a need to develop new models to understand this phenomenon.

There are diverse hypotheses to explain this outcome: routinization, globalization and structural change

Routinization has been proposed by Autor and Dorn (2009), Author (2010) and others authors. The idea is rather simple: some jobs are defined as routine jobs, where there is a clear routine to be carried out. The introduction of ICT has made these jobs partially obsolescent because these technologies are cheaper - and better functioning - in performing routine tasks. Autor and Dorn (2013) stated that "the adoption of computers substitutes for low skill workers performing routine tasks - such as bookkeeping, clerical work, and repetitive production and monitoring activities - which are readily computerized because they follow precise, well-defined procedures". Of course, this hypothesis could be extended to a broad range of jobs and technologies, e.g. the introduction of industrial robots in the automotive industry.

Globalization and offshoring have been pointed out by authors like Goos, Manning and Salomons (2014). The key point is about the likelihood of offshorability of certain tasks and definite jobs. Indeed, together with the routinization hypothesis, "task offshoring -

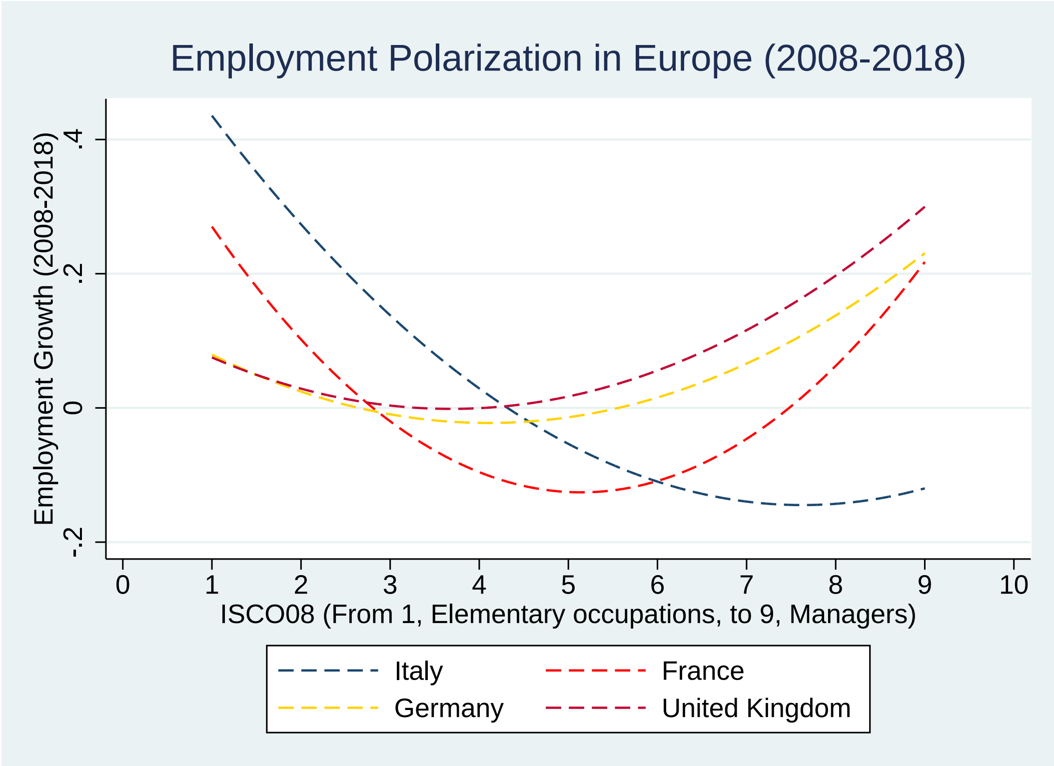

Figure 1: Employment Polarization in Europe (2008-2018)

partially influenced by technological change - decrease the demand for middling relative to high-skilled and low-skilled occupations" (Goos, Manning and Salomons, 2014).

Nonetheless, *routinization* and globalization are closely linked to structural change and related to the declining manufacturing sector, as Bárány and Siegel (2018) have already pointed out. Routine jobs are mostly present in manufacturing and these processes can be easily automated by industrial robots or advanced computers. On the contrary, low-service jobs and high-service jobs are less influenced by the introduction of these technologies and the foreign competition. Indeed, low-end services and high-end services tend to have lower global exposure and, therefore, they experience a lower offshorability risk. This is the reason why this Master's thesis would focus on the interaction between structural change and job polarization.

1.4 Structural change and job polarization

Bárány and Siegel (2018) have deployed a comprehensive view about job polarization and structural change: job polarization is not only a consequence of the adoption of ICT and the globalization at the beginning of 1990, but it has been existing well before. Indeed, the major determinant is the structural transformation of the employment structure of the advanced economies.

In this Master's thesis, I am going to document how major European countries are experiencing similar dynamics to the United States, as already documented by Bárány and Siegel (2018). Structural change is one of the main determinant of job polarization in the United States (Bárány and Siegel, 2018) and this dynamic could be shared with European economies.

Moreover, the inter-sectoral mobility of labor is not occurring without costs and it implies adverse outcomes. In this case, we need to consider two main forces: the adoption of novel technologies and the acquisition of skills to exploit them. This is the so-called race between education and technology, introduced by Goldin and Katz (2007). Greenwood (1997) intuited that workers need time to adopt frontier technologies in the production process. This is also known as Engel's pause (Acemoglu, 2016): it takes time for the workers to understand how to properly apply frontier technologies to the production process and how to efficiently exploit them. Nelson and Phelps (1965) developed a model to clarify the role of human capital in enhancing productivity growth and how human capital is essential in applying frontier technologies to the production process. In this Master's thesis, I am going to argue how different levels of human capital play a fundamental role in defining productivity divergence between European states.

The rest of the paper is organized as follows. Section 2 introduces the economic model developed by Bárány and Siegel (2018). This model is originated around the intuition of Baumol (1967) and it offers a clear explanation of job polarization. Section 3 is aimed at quantitatively assessing the model. It contains a discussion about the used data, the calibration and the quantitative results. Moreover, it investigates the link between job polarization, structural change and productivity slowdown. Section 4 proposes a novel theoretical explanation of the productivity slowdown, based on human capital and structural change. This explanation is based on the Nelson and Phelps (1965) model of human capital and it offers new insights on the effects of structural change and job polarization on productivity. Section 5 concludes the Master's thesis with final remarks on economic growth and technical change.

2 Model

We need to understand the influences of productivity growth and sectoral productivity differentials on wage and employment dynamics, in order to analyze them. Therefore, we rely on the model presented by Bárány and Siegel (2018), a multi-sector growth model with heterogeneous labor in Roy-style fashion, which allows for heterogeneity in wages. In this model, there are three sectors: low-end services, L, manufacturing, M, and high-end services, H. Each sector j produces output, given labor productivity and labor as the only input of the production process. Capital is ruled out from the analysis since the primary interest lies in employment and wage dynamics. Therefore, the production function of the model is given by:

$$Y_j = A_j N_j \quad \text{with} \quad j \in \{L, M, H\} \tag{1}$$

where A_j is productivity and N_j is the total amount of efficiency units of labor hired in sector j for production. We develop this intuition from Baumol (1967). Generally, we observe a structural difference between the productivity of manufacturing and services. Moreover, there is also a structural difference between the productivity of high-end and low-end services, because of the different adaptability of new technologies in each sector: for instance, it is easier to generate greater innovation - and, consequently, higher productivity growth - in fields as banking and financial services than in cleaning or food services. Therefore, we expect to observe a differential in productivity growth between these two different kinds of services.

Firms are price-takers, therefore the equilibrium wage per efficiency unit of labor is the outcome of the following derivation:

$$\omega_j = \frac{\partial p_j Y_j}{\partial N_j} = p_j A_j \quad \text{with} \quad j \in \{L, M, H\} \tag{2}$$

Therefore, wages are determined by prices, p_j, and sectoral productivities, A_j. Given these equilibrium wages per efficiency unit of labor, note that the wage of a worker with a efficiency units of labor of sector j when working in sector j is $a\omega_j$. Prices are determined by the utility maximization problem of the representative household, which collects all the wages earned by individuals and purchase low-end, manufacturing goods and high-end services.

2.1 Labor and demand

The representative household is characterized by a measure of one continuum of different types of members. Indeed, each type is endowed with three exogenous efficiency units and it chooses a specific sectoral labor market in order to get the higher wage per efficiency unit of labor, $a_j\omega_j$, by supplying his one unit of raw labor. Furthermore, the household once collected all the wages of the members, maximize his utility function by consuming low-skilled services, manufacturing goods and high-skilled services.

2.1.1 Sectors

Individuals are heterogeneous, given their endowment of efficiency units of labor, $a \in \mathbf{R}^3_+$, which is drawn from a time-invariant distribution $f(a)$. As in Bárány and Siegel (2018), each dimension corresponds to a specific sector, such that the efficiency units endowments are: $a_l \equiv a(1)$, as efficiency units of labor in low-skilled services, $a_m \equiv a(2)$, in manufacturing and $a_h \equiv a(3)$, in high-skilled services. Therefore, the wage of an individual with $a = (a_l, a_m, a_h)$ efficiency units of labor if working in sector j is $a_j\omega_j$. This endowment a_j is an exogenously distributed skill level for each member of the household, such that there is a heterogeneous distribution of skills among individuals across the economy. As highlighted by Bárány and Siegel (2018), even if this model does not account directly for any form of human capital, one could interpret these endowments as a reduced-form educational choice. Indeed, individuals with high sectoral endowment, a_j are the ones who will acquire formal education or vocational training to enter into the specific sector j. At last, the time-invariant distribution of these exogenous endowments would be a density function $f(a) = f(a_l, a_m, a_h)$ and this is assumed to be a trivariate log-normal distribution. Furthermore, the choice for each agent is determined by the relative wages across sectors:

$$\frac{\omega_l}{\omega_m} \quad \text{and} \quad \frac{\omega_h}{\omega_m}$$

Indeed, the optimal choice for any agent to work in sector j is given by the following system of inequalities:

$$j = L \quad \text{if} \quad a_l \geq \frac{1}{\frac{\omega_l}{\omega_m}} a_m \quad \text{and} \quad a_l \geq \frac{\frac{\omega_h}{\omega_m}}{\frac{\omega_l}{\omega_m}} a_h$$

$$j = M \quad \text{if} \quad a_m \geq \frac{\omega_l}{\omega_m} a_l \quad \text{and} \quad a_m \geq \frac{\omega_h}{\omega_m} a_h$$

$$j = H \quad \text{if} \quad a_h \geq \frac{\frac{\omega_l}{\omega_m}}{\frac{\omega_h}{\omega_m}} a_l \quad \text{and} \quad a_h \geq \frac{1}{\frac{\omega_h}{\omega_m}} a_m$$

We know that agents are maximizing their wages, given their efficiency units of labor: $a_j\omega_j$. For instance, a worker would decide to work for a given sector j if and only if $a_j\omega_j \geq a_i\omega_i$ and $a_j\omega_j \geq a_k\omega_k$. Therefore, for any given wage, workers would self-select the sector j if their efficiency unit of labor for sector j, a_j, is $a_j \geq \frac{\omega_i}{\omega_j} a_i$ and $a_j \geq \frac{\omega_k}{\omega_j} a_k$. Defining wages as relative wages to a third sector gives:

$$a_j \geq \frac{\frac{\omega_i}{\omega_k}}{\frac{\omega_j}{\omega_k}} a_i$$

The optimal sector of work sorting of individuals determines the effective labor supply, given by the efficiency units of labor supplied:

$$N_l\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{\omega_l}{\omega_m} a_l} \int_0^{\frac{\frac{\omega_l}{\omega_m}}{\frac{\omega_h}{\omega_m}} a_l} a_l f(a_l, a_m, a_h) da_h da_m da_l \tag{3}$$

$$N_m\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{1}{\frac{\omega_l}{\omega_m}} a_m} \int_0^{\frac{1}{\frac{\omega_h}{\omega_m}} a_m} a_m f(a_l, a_m, a_h) da_h da_l da_m \tag{4}$$

$$N_h\left(\frac{\omega_l}{\omega_m},\frac{\omega_h}{\omega_m}\right) = \int_0^{\infty}\int_0^{\frac{\frac{\omega_h}{\omega_m}}{\frac{\omega_l}{\omega_m}}a_h}\int_0^{\frac{\omega_h}{\omega_m}a_h} a_h f(a_l,a_m,a_h)da_m da_l da_h \tag{5}$$

The explanation is straightforward. The effective labor supply is given by the set of individuals supplying their one unit of raw labor, weighted for their efficiency units of labor provided to the labor market. This is based on the relative wages, such that individuals self-select a sector j, given the possibility of obtaining the highest $a_j\omega_j$ among different sectors. The effective labor supply in sector j is the total amount of sector j efficiency units, a_j, supplied to that sector. Indeed, the labor supply for the low-end service, L, for instance, is equal to the sum of agents with a high a_l endowment and a relative lower $a_{m,h}$ endowment. The intuition is even clearer from Figure 2:

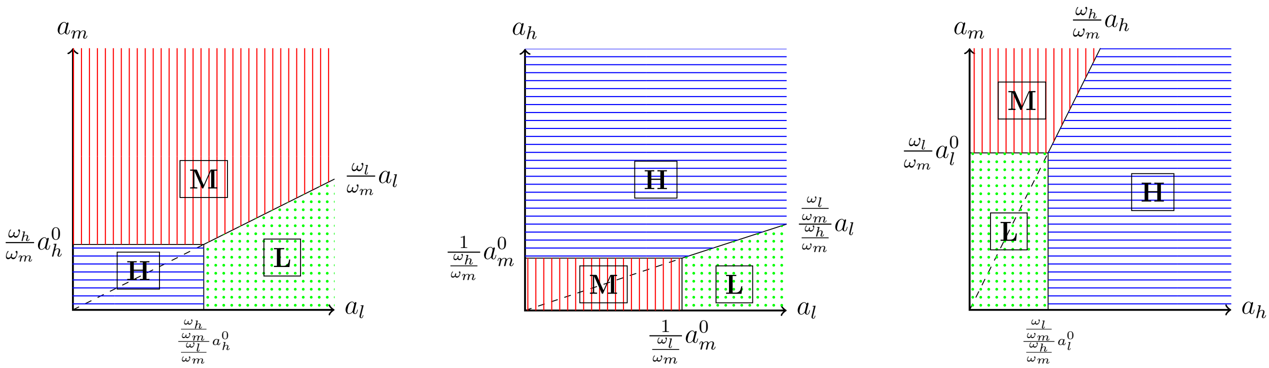

Figure 2: Optimal Sector of Work

Figure 2 represents the optimal sorting behavior of workers in this economy. Indeed, given their efficiency units of labor, a_j, they self-select a sector based on relative wages and relative efficiency units of their other sectoral labor endowments. Therefore, in order to increase the labor supply for a given sector, a rise of relative wages is necessary in order to attract more individuals. A rise of relative wages determines a higher effective labor supply for a given sector. As emphasized by Bárány and Siegel (2018), the effective labor supply is not measurable, but we observe hours worked, which corresponds to the raw labor supply or employment shares L_j in the model. The observed employment shares are the sum of individuals who supply their raw labor unit in a given sector, without weighting it for their efficiency units of labor:

$$L_l\left(\frac{\omega_l}{\omega_m},\frac{\omega_h}{\omega_m}\right) = \int_0^{\infty}\int_0^{\frac{\omega_l}{\omega_m}a_l}\int_0^{\frac{\frac{\omega_l}{\omega_m}}{\frac{\omega_h}{\omega_m}}a_l} f(a_l,a_m,a_h)da_h da_m da_l \tag{6}$$

$$L_m\left(\frac{\omega_l}{\omega_m},\frac{\omega_h}{\omega_m}\right) = \int_0^{\infty}\int_0^{\frac{1}{\frac{\omega_l}{\omega_m}}a_m}\int_0^{\frac{1}{\frac{\omega_h}{\omega_m}}a_m} f(a_l,a_m,a_h)da_h da_l da_m \tag{7}$$

$$L_h\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{\frac{\omega_h}{\omega_m}}{\frac{\omega_l}{\omega_m}} a_h} \int_0^{\frac{\omega_h}{\omega_m} a_h} f(a_l, a_m, a_h) da_m da_l da_h \tag{8}$$

Similarly, ω_l, ω_m and ω_h are not observable. Nonetheless, given that sectoral average wages, $\bar{\omega_j}$, are observable, being total earnings in a sector divided by the mass of people working in the sector (Bárány and Siegel, 2018), we have:

$$\bar{\omega_j} = \frac{\omega_j N_j}{L_j} \equiv \omega_j \bar{a_j} \quad \text{for} \quad j \in \{L, M, H\} \tag{9}$$

2.1.2 Demand

The representative household includes all the members of the economy and it collects their wages. As we previously said, the household maximizes its utility from buying low-end services, manufacturing goods and high-end services, subject to prices (p_l, p_m, p_h) and the sum of wages obtained in each sector from the workers $(\omega_l N_l + \omega_m N_m + \omega_h N_h)$. Indeed, the utility function and the utility maximization problem is determined as:

$$\max_{C_l, C_m, C_h} u\left(\left[\theta_l C_l^{\frac{\varepsilon-1}{\varepsilon}} + \theta_m C_m^{\frac{\varepsilon-1}{\varepsilon}} + \theta_h C_h^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right) \tag{10}$$
$$\text{s.t.} \quad p_l C_l + p_m C_m + p_h C_h \leq \omega_l N_l + \omega_m N_m + \omega_h N_h$$

2.2 Derivation of the equilibrium

In this section, we derive the equilibrium equations given by the utility maximization process subject to prices and wages. For the sake of clarity, we define $A = \theta_l C_l^{\frac{\varepsilon-1}{\varepsilon}} + \theta_m C_m^{\frac{\varepsilon-1}{\varepsilon}} + \theta_h C_h^{\frac{\varepsilon-1}{\varepsilon}}$ and $B = p_l C_l + p_m C_m + p_h C_h - \omega_l N_l - \omega_m N_m - \omega_h N_h$. Moreover, we define $\delta = \frac{\varepsilon-1}{\varepsilon}$ and, therefore, $\frac{1}{\delta} = \frac{\varepsilon}{\varepsilon-1}$. Now, we set up the Lagrangian function:

$$\mathcal{L} = \left(\theta_l C_l^{\frac{\varepsilon-1}{\varepsilon}} + \theta_m C_m^{\frac{\varepsilon-1}{\varepsilon}} + \theta_h C_h^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} + \lambda\left(p_l C_l + p_m C_m + p_h C_h - \omega_l N_l - \omega_m N_m - \omega_h N_h\right)$$

Which is equivalent to say:

$$\mathcal{L} = \left(A\right)^{\frac{1}{\delta}} + \lambda\left(B\right)$$

Therefore, we define four Lagrangian equations of partial derivatives:

$$\frac{\partial \mathcal{L}}{\partial C_l} = \frac{1}{\delta}\left(A\right)^{\frac{1-\delta}{\delta}} \delta \theta_l C_l^{\delta-1} + \lambda p_l = 0$$

$$\frac{\partial \mathcal{L}}{\partial C_m} = \frac{1}{\delta}\Big(A\Big)^{\frac{1-\delta}{\delta}} \delta\theta_m C_m^{\delta-1} + \lambda p_m = 0$$

$$\frac{\partial \mathcal{L}}{\partial C_h} = \frac{1}{\delta}\Big(A\Big)^{\frac{1-\delta}{\delta}} \delta\theta_h C_h^{\delta-1} + \lambda p_h = 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = p_l C_l + p_m C_m + p_h C_h - \omega_l N_l - \omega_m N_m - \omega_h N_h = 0$$

Indeed, we obtain a system of four equations:

$$\begin{cases} A^{\frac{1-\delta}{\delta}}\theta_l C_l^{\delta-1} + \lambda p_l = 0 \\ A^{\frac{1-\delta}{\delta}}\theta_m C_m^{\delta-1} + \lambda p_m = 0 \\ A^{\frac{1-\delta}{\delta}}\theta_h C_h^{\delta-1} + \lambda p_h = 0 \\ p_l C_l + p_m C_m + p_h C_h - \omega_l N_l - \omega_m N_m - \omega_h N_h = 0 \end{cases}$$

Under equilibrium and market-clearing conditions, $p_j = \frac{\omega_j}{A_j}$ and $C_j = A_j N_j$:

$$\frac{\omega_l}{A_l} A_l N_l + \frac{\omega_m}{A_m} A_m N_m + \frac{\omega_h}{A_h} A_h N_h - \omega_l N_l - \omega_m N_m - \omega_h N_h = 0$$

And, therefore, the first equilibrium equation relative to low-end services is given by the following equation:

$$A^{\frac{1-\delta}{\delta}} = \frac{-\lambda p_m}{\theta_m C_m^{\delta-1}}$$

$$\frac{-\lambda p_m}{\theta_m C_m^{\delta-1}}\theta_l C_l^{\delta-1} + \lambda p_l = 0 \quad \rightarrow \quad -\lambda p_m \theta_l C_l^{\delta-1} = -\lambda p_l \theta_m C_m^{\delta-1}$$

$$\frac{C_l^{\delta-1}}{C_m^{\delta-1}} = \frac{-\lambda p_l \theta_m}{-\lambda p_m \theta_l} \quad \rightarrow \quad \left(\frac{C_l}{C_m}\right)^{\delta-1} = \frac{p_l \theta_m}{p_m \theta_l} \quad \text{with} \quad \delta - 1 = \frac{\varepsilon - 1}{\varepsilon} - 1 = -\frac{1}{\varepsilon}$$

$$\left(\frac{C_l}{C_m}\right)^{-\frac{1}{\varepsilon}} = \frac{p_l \theta_m}{p_m \theta_l} \quad \rightarrow \quad \frac{C_l}{C_m} = \left(\frac{p_l \theta_m}{p_m \theta_l}\right)^{-\varepsilon}$$

And the second equilibrium equation relative to high-end services is given by the following equation:

$$\frac{-\lambda p_m}{\theta_m C_m^{\delta-1}}\theta_h C_h^{\delta-1} + \lambda p_h = 0 \quad \rightarrow \quad -\lambda p_m \theta_h C_h^{\delta-1} = -\lambda p_l \theta_m C_m^{\delta-1}$$

$$\frac{C_h^{\delta-1}}{C_m^{\delta-1}} = \frac{-\lambda p_h \theta_m}{-\lambda p_m \theta_h} \quad \rightarrow \quad \left(\frac{C_h}{C_m}\right)^{\delta-1} = \frac{p_h \theta_m}{p_m \theta_h} \quad \text{with} \quad \delta - 1 = \frac{\varepsilon - 1}{\varepsilon} - 1 = -\frac{1}{\varepsilon}$$

$$\left(\frac{C_h}{C_m}\right)^{-\frac{1}{\varepsilon}} = \frac{p_h \theta_m}{p_m \theta_h} \quad \rightarrow \quad \frac{C_h}{C_m} = \left(\frac{p_h \theta_m}{p_m \theta_h}\right)^{-\varepsilon}$$

Hence, the two equilibrium equations, which are maximizing the utility function given prices and wages, as already presented in Bárány and Siegel (2018), are:

$$\frac{C_l}{C_m} = \left(\frac{p_l}{p_m}\frac{\theta_m}{\theta_l}\right)^{-\varepsilon} \tag{11}$$

$$\frac{C_h}{C_m} = \left(\frac{p_h}{p_m}\frac{\theta_m}{\theta_h}\right)^{-\varepsilon} \tag{12}$$

These equations are fundamental for understanding the mechanism of differential sectoral productivities and structural change.

2.3 Equilibrium

Under optimal decision and markets clearing, the equilibrium is specified by wages, prices, consumption demands, endogenously determined by the model implied productivities, A_j. Indeed, the market clears, $Y_j = C_j = A_j N_j$ for $j \in \{L, M, H\}$, and we obtain from equation (11) and (12) that:

$$\frac{A_l}{A_m}\frac{N_l}{N_m} = \left(\frac{\omega_l}{\omega_m}\frac{A_m}{A_l}\frac{\theta_m}{\theta_l}\right)^{-\varepsilon} = \left(\frac{p_l}{p_m}\frac{\theta_m}{\theta_l}\right)^{-\varepsilon} \tag{13}$$

$$\frac{A_h}{A_m}\frac{N_h}{N_m} = \left(\frac{\omega_h}{\omega_m}\frac{A_m}{A_h}\frac{\theta_m}{\theta_h}\right)^{-\varepsilon} = \left(\frac{p_h}{p_m}\frac{\theta_m}{\theta_h}\right)^{-\varepsilon} \tag{14}$$

Note that:

$$p_j = \frac{\omega_j}{A_j} \quad \rightarrow \quad \frac{p_j}{p_i} = \frac{\omega_j}{A_j}\frac{A_i}{\omega_i} = \frac{\omega_j}{\omega_i}\frac{A_i}{A_j}$$

(13) and (14) are the most important features of this model. A change in the relative sectoral productivity, $\frac{A_j}{A_i}$, when A_i grows faster than A_j, generates two relevant effects: (i) a supply effect, on the left-hand side of the equation, reduces the relative output, $\frac{Y_j}{Y_i}$, and (ii) the demand effect, which increases the demand, $\frac{\omega_j}{\omega_i}\frac{A_i}{A_j}$, on the right-hand side of the equation. Therefore, the effect is two-fold: on one hand, it increases the relative supply of a sectoral output relative to other sectors; on the other hand, higher productivity drives down relative prices, generating higher demand for both goods. If goods are complements, $\varepsilon < 1$, the demand effect is weaker and, therefore, the relative supply falls by more than relative demand. Further, to restore the equilibrium, the lagging sector should start employing more workers and N_j must increase to offset this disequilibrium. This is exactly what Baumol (1967) has highlighted: the most productive sector would shrink in terms of employment, while the lagging sector needs to employ more workers to cope with the higher relative demand. Indeed, using the optimal sorting of workers from

equations (3), (4) and (5), we obtain:

$$\frac{N_l\left(\frac{\omega_l}{\omega_m},\frac{\omega_h}{\omega_m}\right)}{N_m\left(\frac{\omega_l}{\omega_m},\frac{\omega_h}{\omega_m}\right)}\left(\frac{\omega_l}{\omega_m}\right)^{\varepsilon}=\left(\frac{A_m}{A_l}\right)^{1-\varepsilon}\left(\frac{\theta_m}{\theta_l}\right)^{-\varepsilon} \tag{15}$$

$$\frac{N_h\left(\frac{\omega_l}{\omega_m},\frac{\omega_h}{\omega_m}\right)}{N_m\left(\frac{\omega_l}{\omega_m},\frac{\omega_h}{\omega_m}\right)}\left(\frac{\omega_h}{\omega_m}\right)^{\varepsilon}=\left(\frac{A_m}{A_h}\right)^{1-\varepsilon}\left(\frac{\theta_m}{\theta_h}\right)^{-\varepsilon} \tag{16}$$

Therefore, when the two types of services are complements with manufacturing goods ($\varepsilon < 1$), the faster relative productivity of manufacturing generates a transition in the optimal sorting of individuals in each sector. Indeed, the lagging sector needs to attract more workers to restore the equilibrium and, therefore, relative wages, $\frac{\omega_l}{\omega_m}$ and $\frac{\omega_h}{\omega_m}$, rise. At the same time, a rise of sectoral wages implies an increase of sectoral prices, lowering its demand. This process leads to a wage and employment polarization among sectors, as documented in Bárány and Siegel (2018).

3 Data and Quantitative Results

In this section, we calibrate the model for four major European countries: the United Kingdom, Italy, Germany and France.

At first, we evaluate data from these countries, analyzing its characteristics and its common features.

Then, we present the calibration of the parameters, as performed by Bárány and Siegel (2018): first, we match the key moments in 1970 to generate a specific distribution function of endowments $f(a_l, a_m, a_h)$ such that employment shares and average sectoral wages are met with data. Then, we generate a prediction about the evolution of employment and wages given exogenous productivity growth, while comparing it with the actual data for the period 1970-2015. The calibration of the model allows us to understand the similarities and the differences between European economies and the United States.

We find that European economies are experiencing job polarization mainly because of structural change and inter-sectoral productivity differentials. This is in line with the results of Bárány and Siegel (2018) for the United States.

Nonetheless, the model calibrated with European data performs poorly relative to data from the United States. This may be cause by the role of the common market and its effects on the domestic demand and the foreign competition: indeed, this model describe a closed economy and it does not consider international trade.

At last, we are presenting the quantitative results of this calibration, discussing the mechanism driving this phenomenon and its implications. In conclusion, structural change is a main determinant of employment polarization in European economies.

3.1 Data

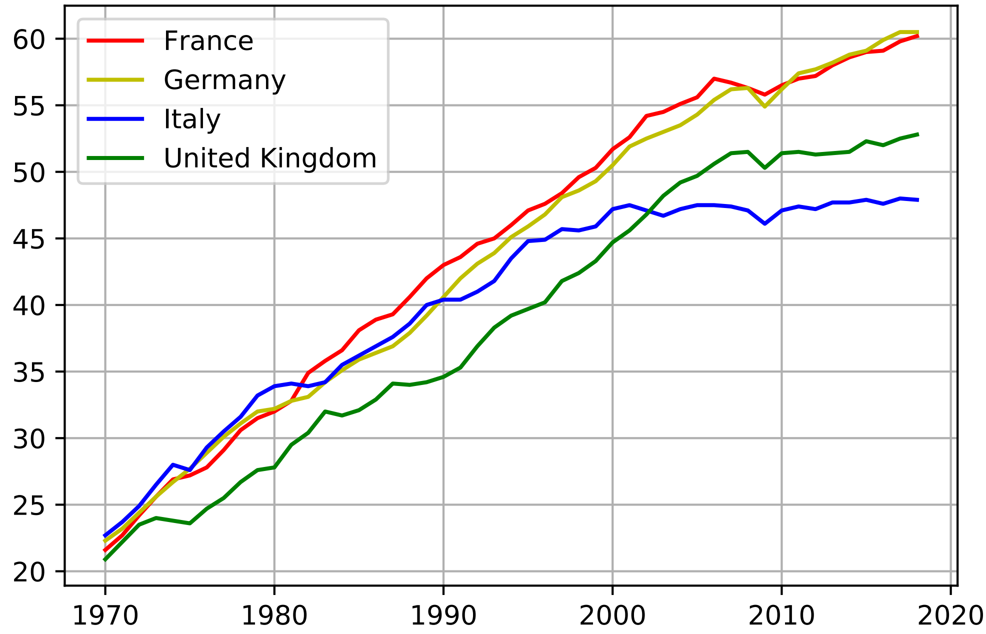

Figure 3: Labor productivity (GDP per hour worked, US Dollars, 1970-2018), Source: OECD

Figure 3 shows labor productivity, measured as Gross Domestic Product (GDP) per hour worked, in Germany, France, Italy and the United Kingdom over the past decades. This figure attests that Italy and the United Kingdom have experienced a long period of stagnation of productivity growth for, respectively, 20 and 10 years, while France and Germany are still following a positive steady trend. France and Germany are, indeed, still at the same productivity level of the United States, while Italy and the United Kingdom are lagging well behind. Nonetheless, even France (Askenazy, 2015) and Germany (Elstner, 2018), together with the United States (Sichel, 2017), are struggling to gain a higher productivity growth: in fact, labor productivity is noticeably slowing down in all advanced economies. The academic literature has recently developed a considerable debate about the phenomenon of the productivity slowdown. Following Gordon (2012), diverse authors highlighted the incapability of Information and Communication Technologies (ICT) for generating stronger productivity growth: this phenomenon, better known as the return of the Solow Paradox, has already been evidenced in the United States (Acemoglu et al., 2014). Moreover, the introduction of innovative products and novel equipment, as advanced computer software, has not implied a rise in labor productivity in the last decades. These dynamics may lead the global economy towards a secular stagnation (Gordon, 2015; Summers, 2014). In fact, labor productivity growth is essential to sustain higher prospects, higher employment growth and higher economic growth. Moreover, as we have highlighted in the previous section, productivity growth is the main driver of employment generation, wage growth and structural change in our model. Therefore, it is essential to fully characterize how productivity differs among these countries.

Data are selected from the EU KLEMS Growth and Productivity Accounts (Jäger, 2018). This database contains a large selection of growth and productivity measures for different European countries around a large time set (1970-2015). Most importantly, we are interested in labor productivity, employment and wage measures to calibrate the model.

Following Ngai and Petrongolo (2014) and Bárány and Siegel (2018), we measure labor productivity as Gross Value Added (GVA) per hour worked, employment shares as the sectoral number of hours worked and, at last, sectoral wages as sectoral labor compensation using EU KLEMS Data. GVA is particularly efficient because: (i) it excludes taxes, while GDP per hour worked does not and it could distort our measures, and (ii) hours worked are more appropriate than total employment because they could account for variation in average hours worked during the business cycle (OECD, 2019).

We define three main sectors, following Bárány and Siegel (2018), from ISIC Rev. 4 industry classification: low-skilled services, L, is a set of $J, I, H, O-U$, manufacturing, M, contains B, C, D, E, F and high-skilled services, H, includes $K, L, M-N$. These classifications are completely summarized in Table 2.

Table 2: ISIC Rev. 4 Industry Classification

WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES	G	L
TRANSPORTATION AND STORAGE	H	
ACCOMMODATION AND FOOD SERVICE ACTIVITIES	I	
COMMUNITY SOCIAL AND PERSONAL SERVICES	O-U	
MINING AND QUARRYING	B	M
TOTAL MANUFACTURING	C	
ELECTRICITY, GAS AND WATER SUPPLY	D-E	
CONSTRUCTION	F	
INFORMATION AND COMMUNICATION	J	H
FINANCIAL AND INSURANCE ACTIVITIES	K	
REAL ESTATE ACTIVITIES	L	
PROFESSIONAL, SCIENTIFIC, TECHNICAL, ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES	M-N	

Furthermore, using the previous classification, we computed each relevant measure for the time 1970-2015. This comprises average sectoral productivity growth, employment share for each sector and average sectoral labor compensation. To get these measures, we used two different EU KLEMS dataset for obtaining a complete-time set from 1970 to 2015. These data-sets are September 2017 release, Revised July 2018 and 2012 Release EU KLEMS.

All parameters are constant in time, and the unique exogenous change over time is labor productivity growth $\Big(A_j \text{ with } j \in \{L, M, H\}\Big)$. We are interested in five key moments: the relative average sectoral wages, $\frac{w_h}{w_m}$ and $\frac{w_l}{w_m}$, and the sectoral employment shares, L_l, L_m, and L_h, which sum to one. Further, we need to calibrate the following parameters: those of the utility function, θ_L, θ_M and θ_H, the distribution of labor efficiencies, $f(a_L, a_M, a_H)$, and the initial sectoral labor productivites, $A_l(0)$, $A_m(0)$ and $A_h(0)$, in 1970.

We perform the same procedure as the original paper (Bárány and Siegel, 2018). At first, we calibrate the distribution of efficiency units of labor endowments in order to match the employment shares and the relative average sectoral wages observed in data in 1970. Second, given this distribution, we calibrate the utility function and the initial productivity parameters. Then, starting from the calibrated initial productivity parameters, we generate a path for the model-implied labor productivity using measured labor productivity as a target. Therefore, the path of the model-implied labor productivity is following the same path of the measured labor productivity. In this way, we are accounting for the difference between N_j and L_j, reducing the self-selection bias. Using this method, we are able to generate a prediction for the employment shares and the relative average wage trends, making them comparable with actual data.

Table 3: Calibrated Parameters

	Description	Value
ρ_{lm}	Correlation between L and M sector efficiency	0.3
ρ_{lh}	Correlation between L and H sector efficiency	0.3
ρ_{mh}	Correlation between M and H sector efficiency	0.3
σ_l^2	Variance of L sector efficiency	0.12
σ_m^2	Variance of M sector efficiency	0.30
σ_h^2	Variance of H sector efficiency	0.35
ε	CES between L, M, and H in consumption	0.002

Table 3 summarizes the calibrated parameters, as taken from the literature and the original paper. We opted to use the parameters of Bárány and Siegel (2018) because these four countries are comparable with the United States. The Constant Elasticity of Substitution (CES) between sectors is estimated in the range (0, 0.3) (Ngai and Pissarides, 2008). As performed in the original paper, we rely on the estimate of Herrendorf, Rogerson, and Valentinyi (2013), $\varepsilon = 0.002$.

The labor productivity growth measures are discussed for each country in the following section. As assumed in Bárány and Siegel (2018), labor efficiencies are drawn from a trivariate lognormal distribution. The original paper presents a careful discussion of this assumption (Bárány and Siegel, 2018). This parametrization ensures that the distribution of wages is similar to the real distribution of wages, as evidenced by many studies. In fact, the lognormal distribution comprises a fat right tail, which is often observed in data on wage distributions. At last, the normalized mean of each element (a_l, a_m, a_h) of the distribution is assumed to be unity. Furthermore, as performed in Bárány and Siegel (2018), the model output can be written as $Y_j = A_j N_j = B_j L_j$ for each sector j. However, we only observe L_j and B_j. Therefore, we need for accounting for the difference between N_j, the effective labor supply, and L_j, the raw employment shares (hours worked), the so-called selection effect. Indeed, the self-selection process does bias the model-implied labor productivity and effective labor supply because individuals with higher endowments self-select specific sectors, raising its model implied productivity level. To get rid of this bias, we compute the path of A_j in the following way: given the calibration of all of the fixed parameters of the model, we find the path of A_j, the model-implied labor productivity, such that the model implied growth in B_j is equal to the labor productivity growth measured in the data. Further, if initial A_j is calibrated in order to get the employment shares, its growth path is generated by targeting the observed growth path of the measured labor productivity.

3.1.1 Italy

There is an extensive literature identifying Italy as one of the most interesting examples of productivity slowdown and growth issues over recent decades (Fachin and Gavosto, 2010; Daveri and Lasinio, 2005). Consistent with the hypothesis of unbalanced growth (Baumol, 1967), labor productivity growth of Italian manufacturing is structurally higher than labor productivity growth of high- and low-end services. This is also evidenced in the data of the United States (Bárány and Siegel, 2018). Nonetheless, manufacturing productivity growth has slowed down during the decade 2000 - 2010: this is caused from the dramatic impact of the Financial Crisis and the Sovereign Debt Crisis, followed by a strong credit crunch, on industrial production (Busetti et al., 2014), implying lower productivity growth of this sector.

Data on Italian labor productivity growth features an interesting fact: the overall growth of high-end services over this period is slightly negative. Indeed, this has been caused from a massive drop in labor productivity during the 1980-1990 decade, which has not been followed by a significant rise over the following decades. This is one of the main drivers of the marked decline of Italian productivity, started from 1980 onwards.

Figure 4 highlights that the most important determinants of productivity slowdown are Real Estate Activities and Professional, Scientific, Technical, Administrative and Support Services Activities. Daveri and Lesinio (2005) indicates that services are still plagued by extensive monopolistic provision and, therefore, a weak productivity perfor-

Table 4: Decennial Average Labor Productivity Growth, measured as decennial average of $B_{j,t}/B_{j,t-1}$, and weighted geometric mean (Italy, 1970-2015)

	B_l	B_m	B_h
1970-1980	1.0145	1.0214	1.0044
1980-1990	0.9954	1.0215	0.9586
1990-2000	1.0152	1.0186	1.0051
2000-2010	0.9982	0.9976	1.0048
2010-2015	1.0025	1.0275	1.0018
1970-2015	**1.0054**	**1.0161**	**0.9939**

mance is not surprising. Moreover, in these sectors, productivity has been largely higher in the 1970s than nowadays. Hassan and Ottaviano (2013) suggest that decreasing productivity in Italy may be caused by within-sector misallocation of resources, following Daveri and Lesinio (2005). Furthermore, Daveri and Lesinio (2005) found evidence that the productivity slowdown manifested itself together with two phenomena: “the presence of a high share of temporary workers and the old age and high seniority of top managers and members of the boards”. This is in line with the model we are proposing in Section 5. Indeed, skills and human capital acquisition are essential in determining steady productivity growth and higher inter-sectoral mobility of labor may be detrimental to productivity growth.

Table 5: The productivity gap between Italy and other European Countries (1970-2015)

	$B_l - B_l$			$B_m - B_m$			$B_h - B_h$		
	France	Germany	UK	France	Germany	UK	France	Germany	UK
1970-1980	-0.013	-0.008	0.007	-0.040	-0.004	-0.006	-0.014	-0.025	-0.008
1980-1990	-0.019	-0.008	-0.008	-0.000	0.008	-0.021	-0.055	-0.057	-0.042
1990-2000	-0.004	0.001	-0.005	-0.006	-0.002	-0.051	-0.007	-0.016	-0.025
2000-2010	-0.006	-0.018	-0.011	0.002	-0.018	-0.003	-0.013	-0.005	-0.015
2010-2015	-0.002	0.003	0.000	0.026	0.024	0.029	-0.010	-0.004	-0.005

Table 5 shows the productivity growth gap between Italy and the other European countries. The productivity growth gap between these countries is relevantly large for high-skilled services, where Italian productivity growth has constantly under-performed relative to its partners. The manufacturing sector has over-performed in the last decade and it is generally in line with other European economies. This dynamic is evident even for low-skilled service. Consequently, one of the main determinants of the productivity slowdown in Italy is the increasing importance of the high-skilled service sector in terms of employment and output, following structural change, and the inability of generating higher productivity growth in this sector.

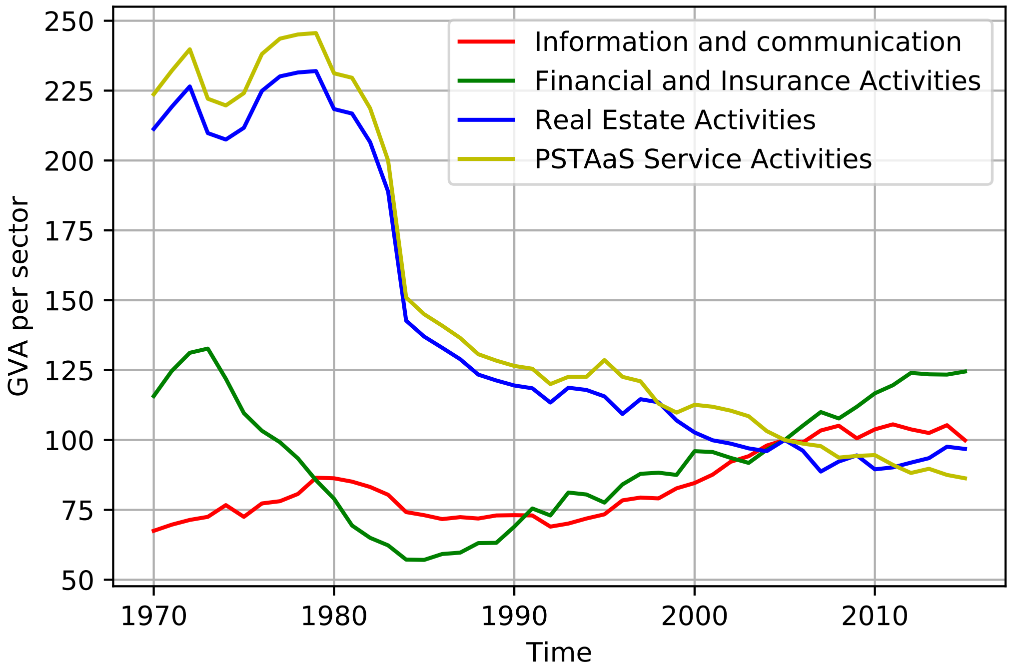

Figure 4: Within B_h productivity, Italy (Index=2005)

3.1.2 Germany

Table 6: Decennial Average Labor Productivity Growth, measured as decennial average of $B_{j,t}/B_{j,t-1}$, and weighted geometric mean (Germany, 1970-2015)

	B_l	B_m	B_h
1970-1980	1.0228	1.0260	1.0302
1980-1990	1.0113	1.0135	1.0164
1990-2000	1.0139	1.0214	1.0216
2000-2010	1.0166	1.0160	1.0099
2010-2015	0.9988	1.0034	1.0067
1970-2015	**1.0141**	**1.0174**	**1.0180**

Germany features a high average of high-skilled services productivity growth over the entire period. Moreover, as we have already evidenced for the United States and Italy, labor productivity growth in manufacturing is structurally higher than low-end and high-end services. Germany experienced a remarkable decline of productivity growth in each sector from 2010 onwards (Elstner, 2018). Elstner (2018) suggests that these dynamics are linked with the successful integration of five million predominantly low-productivity workers into the labor market. This has induced a marked slowdown of labor productivity growth. Moreover, Elstner (2018) finds that "technological progress originating in the ICT-producing sector has significant positive effects on GDP and employment. The net effect on labor productivity, however, is modest. Consequently, increasing digitization leads to higher production and employment, but not too sizeable higher productivity". This is again related to the so-called return of the Solow Paradox. Further, it is evident that productivity slowed in the last decades, as observed in other advanced economies: most importantly, from the Financial Crisis onwards.

3.1.3 France

Table 7: Decennial Average Labor Productivity Growth, measured as decennial average of $B_{j,t}/B_{j,t-1}$, and weighted geometric mean (France, 1970-2015)

	B_l	B_m	B_h
1970-1980	1.0276	1.0624	1.0186
1980-1990	1.0227	1.0225	1.0142
1990-2000	1.0197	1.0252	1.0128
2000-2010	1.0043	0.9948	1.0186
2010-2015	1.0053	1.0009	1.0120
1970-2015	**1.0170**	**1.0231**	**1.0155**

The productivity growth of low-end services and manufacturing, both initially higher than high-end services, declined remarkably from 2000 onwards. As previously observed, France experiences productivity slowdown in both low-end services and manufacturing. Nonetheless, as we have previously observed in other countries, the labor productivity growth of French manufacturing is structurally higher over the period 1970-2000. Askenazy (2015) suggests that labor market mechanisms are better candidates for explaining the French productivity slowdown. French labor market policy has generated a marked increase in low-productive jobs, including very-short-term employees and self-employed workers (Askenazy, 2015). Again, this could be easily related to the capability of acquiring novel skills and human capital: very-short-term employees and self-employed workers may be less exposed to training and human capital acquisition programs.

3.1.4 United Kingdom

United Kingdom's data features the highest growth of high-end services productivity in the period 1990-2010 relative to the other examined countries. Moreover, the productivity growth of the British manufacturing sector is extremely high in the period 1970-2000, while decreasing drastically from 2000 onwards. Low-end services, as seen even in other countries, features a structurally low productivity growth. Tenreyro (2018) has explained that:

- Two sectors, finance and manufacturing, can account for most of the fall in overall UK productivity growth in the last decade.

Table 8: Decennial Average Labor Productivity Growth, measured as decennial average of $B_{j,t}/B_{j,t-1}$, and weighted geometric mean (United Kingdom, 1970-2015)

	B_l	B_m	B_h
1970-1980	1.0067	1.0281	1.0128
1980-1990	1.0113	1.0430	1.0014
1990-2000	1.0203	1.0698	1.0303
2000-2010	1.0098	1.0008	1.0207
2010-2015	1.0018	0.9978	1.0076
1970-2015	**1.0108**	**1.0309**	**1.0152**

- "The post-crisis productivity drag from finance should disappear as deleveraging runs its course. Slower manufacturing productivity growth may relate to a reduction in the impact of lower-priced imported inputs from China and other emerging markets".
- "Weak investment has also been playing an increasingly important role in the weakness of manufacturing and aggregate productivity".

Table 8 makes it evident. From 2000 onwards, there is a drastic decline in B_m and it is followed by a marked decrease of B_h in the period 2010-2015.

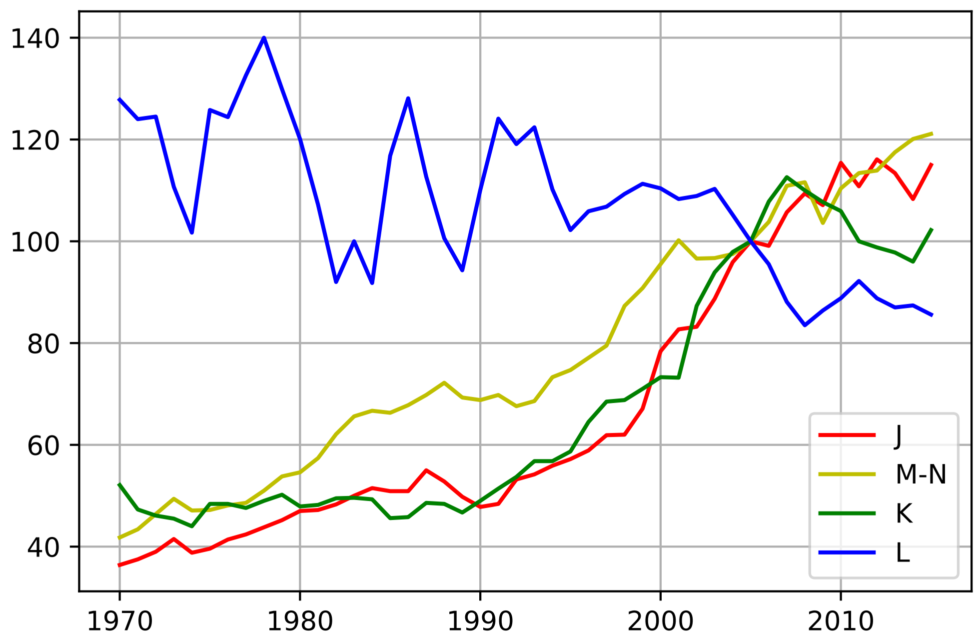

Figure 5: Within B_h productivity, United Kingdom (Index=2005)

Figure 5 shows, as previously done with Figure 4, productivity growth in different sectors among B_h. It is evident that the productivity of L, Real Estate Activities, has not been increasing during this time. Moreover, K, Financial and Insurance Activities, experienced a large decline in productivity levels after the financial crisis, as previously mentioned (Tenreyro, 2018).

3.2 Concluding Remarks

In the last decades, France and the United Kingdom have experienced higher productivity growth in high-end service, B_h, than in manufacturing, B_m. This could tell us something more about the intuition of Baumol (1967). Sectors, which were previously considered as low productive and with little space for innovation, may start to deploy modern technologies, generating higher productivity growth. Indeed, as highlighted by Brynjolfsson and McAfee (2014), modern technologies have the capability to create impressive gains in terms of productivity growth for high-end and low-end services.

One important feature of the analyzed data is that technology is not the unique source of productivity improvements. Each country experienced a large decline in productivity during the $2000-2010$ and $2010-2015$, after the impact of the Financial Crisis and the consequent Great Depression. This has influenced productivity growth and it may be possible that it interacted with other features, such as globalization and technological progress. As we have already stated, demand plays a pivotal role in determining productivity growth.

At last, one consideration about the notion of Engel's Pause (Acemoglu, 2016). Acemoglu (2016) has shown that there are strong parallels with the beginning of the Industrial Revolution around 1760, where there was no wage growth, despite a strong technological change and technical adoption in Great Britain, and with the rapid technological advancement we are witnessing from the beginning of this century. In fact, this may be caused by the fact that novel technologies were not properly implemented and the productivity gains were not fully realized, until later after the process of learning by doing and experimentation was completed (Acemoglu, 2016).

3.3 Quantitative results and calibration

In this section, we present the results of the calibration for four different European countries, following the procedure of Bárány and Siegel (2018). The original paper has presented model calibrated with United States' data from 1960 to 2007. By contrast, we start our calibration from 1970 and we extend it to 2015, adding further insight into the role of structural change on employment and wage polarization. As highlighted by Bárány and Siegel (2018), our ultimate interest is the endogenous path of employment shares and relative average wages.

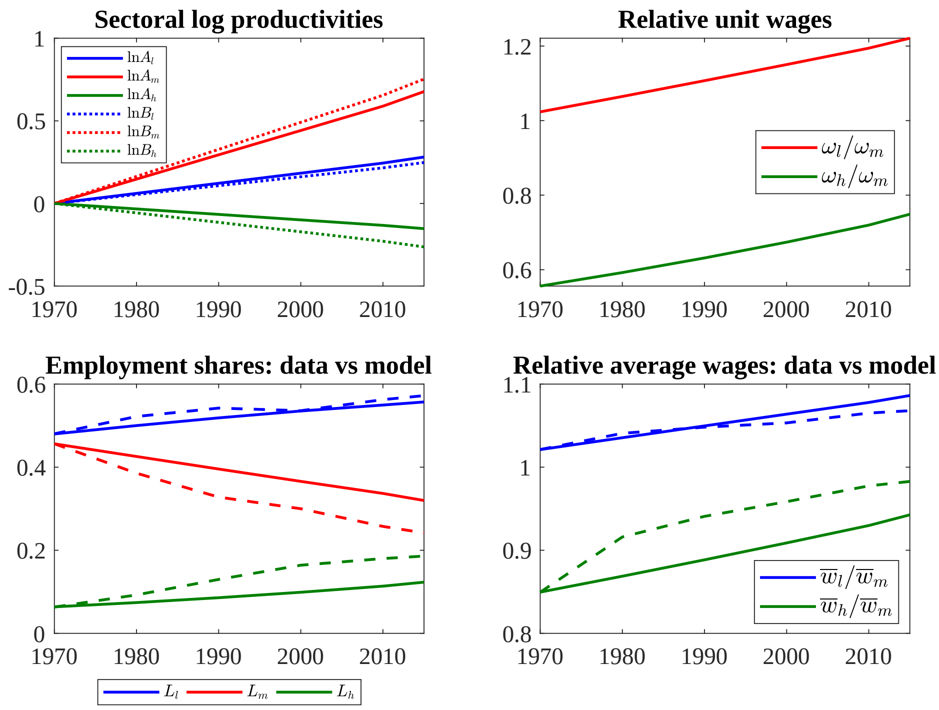

Figure 6: **Italy**: data (dashed) vs. model (1970-2015)

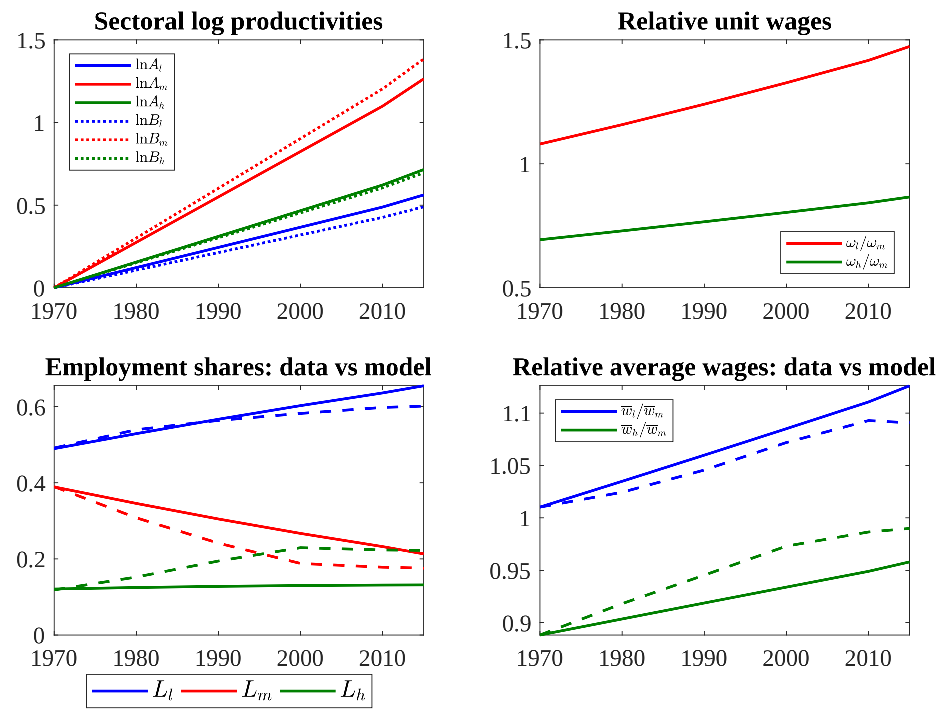

Figure 7: **United Kingdom**: data (dashed) vs. model (1970-2015)

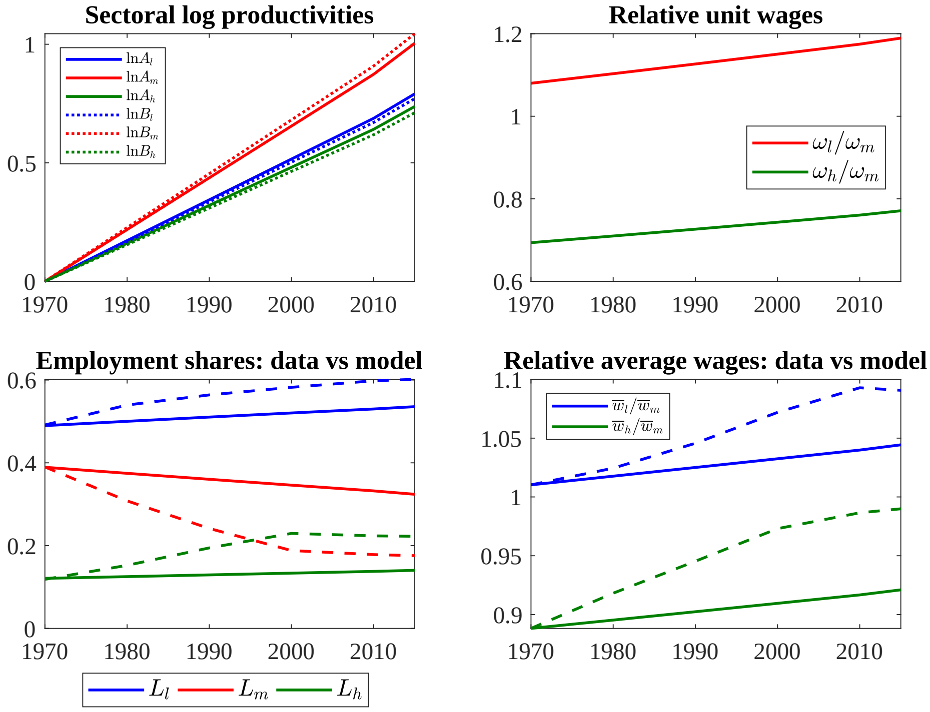

Figure 8: **France**: data (dashed) vs. model (1970-2015)

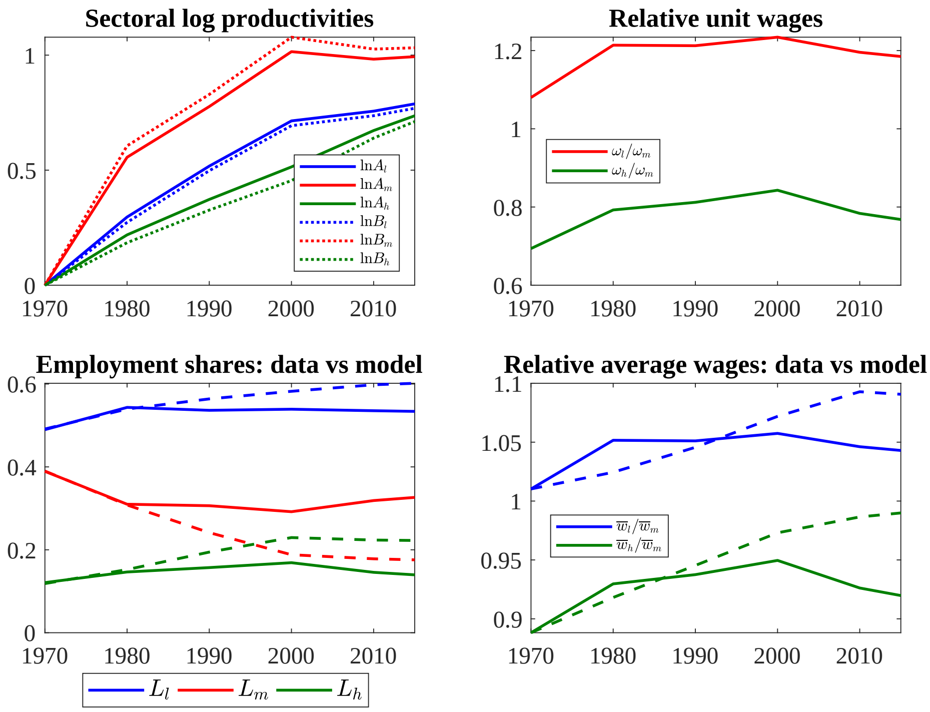

Figure 9: **France**: data (dashed) vs. model (1970-2015) - Decennial productivity growth

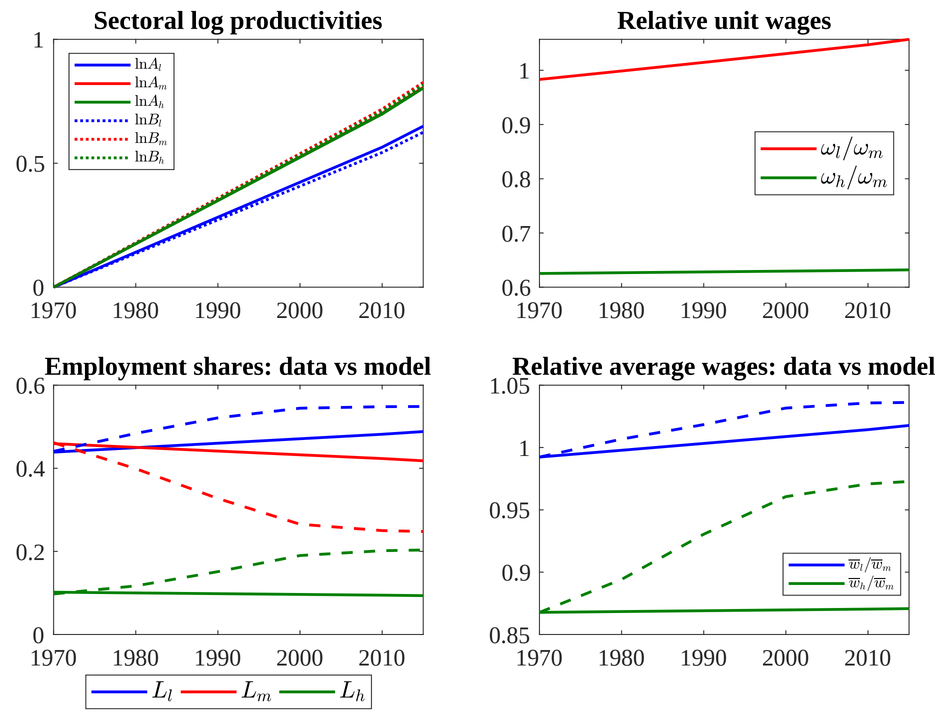

Figure 10: **Germany**: data (dashed) vs. model (1970-2015)

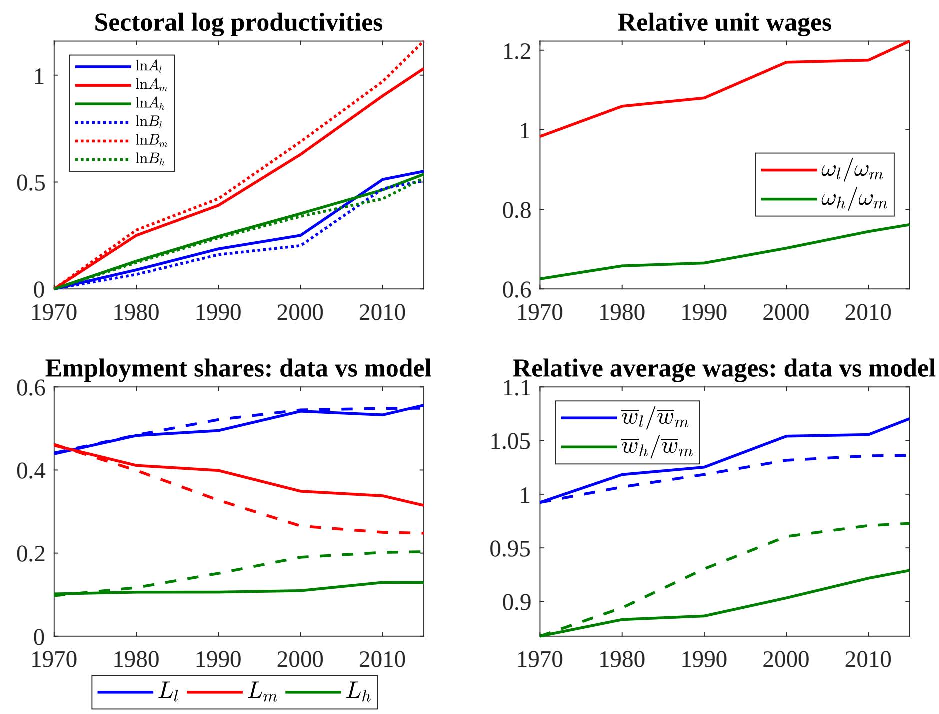

Figure 11: **Germany**: data (dashed) vs. model (1970-2015) - Decennial productivity growth

3.3.1 Discussion of the results

Figure 6 shows the calibration of the model calibrated on Italian data. The model predicts accurately both employment shares and wage growth for the period 1970-2015. The strong inter-sectoral productivity growth differential in Italy is the main driver of the large decline in manufacturing employment. This inter-sectoral differential is evident even for the United Kingdom. Figure 7 shows the predictions of the model matching British data. In this case, the British economy experienced a higher decline in manufacturing employment than the Italian economy, but stronger productivity growth in high-skilled services. The model predicts accurately both employment shares and wage dynamics.

According to Figure 8, the model does not predict as well as previous countries the dynamics of the French economy. This may be caused by the strong average productivity growth of the French economy during the period 1970-2015. As we have previously seen, this average could be distorted by the strong productivity growth of the early decades. Following the procedure of Bárány and Siegel (2018), we decided to plug in decennial growth rates. This is depicted in Figure 9. Moreover, sectoral productivity growth paths are clearly showing a productivity slowdown for each sector. The calibration becomes more precise by plugging in decennial growth rates. Nonetheless, the model is over-predicting the employment in manufacturing and under-predicting the employment in high-skilled services. This may be caused by the structure of the model, which we will discuss further at the end of the section.

Germany, as shown by Figure 10, has average productivity growth for manufacturing and high-skill services at a similar level. Since the model is not accurately predicting employment shares and wage growth under these circumstances, the proposed model has a drawback: it needs a strong inter-sectoral productivity growth differential to properly predict observed data. As previously performed with French data, we plug in decennial growth rates, in order to obtain Figure 11. This method is effective with German data and the predictions are in line with observed data.

The model does remarkably well in predicting employment shares and wage growth, as shown in Bárány and Siegel (2018). However, we can observe some drawbacks, as previously mentioned. In fact, there is an important common feature in these calibrations. The model over-predicts the employment change of manufacturing jobs while under-predicting it for high-skilled services. This is evident even where we decided to plug in decennial growth rates. This could be caused by different features of the economy and we are able to formulate hypotheses about these features. One explanation requires us to understand the model. This model describes a closed economy, without any foreign competition or international trade. We could argue that the creation of the Single European Market has impacted on the generation of jobs on both high-end services and manufacturing. Further, increased foreign competition and trade openness has impacted negatively on manufacturing employment, but it has benefited high-end services employment. Foreign competition could even impact both on prices and demand, by reducing domestic demand and, at the same time, reducing prices. While, at the same time, the increasing importance of high-end services in advanced economies has determined higher gains caused by the internationalization of this sector.

Demand, as denoted in this model, is fundamental to determine prices and therefore, the structural change mechanism, as highlighted by equations (13) and (14). What is the role of the link between wages, productivity and demand? In this framework, (i) wages are determined by productivity and, therefore, a productivity slowdown implies a wage stagnation, as observed in European economies and (ii) a productivity slowdown (or higher inter-sectoral productivity differentials) in (13) and (14) may be offset by two mechanisms: an increase of the labor demand for the lagging sector, but also a decrease of wages in the sector with high productivity growth.

There are three important takeaways from this model: (i) demand matters in determining productivity growth and, therefore, as a driver of employment generation and relocation of workers. Technology is not the only determinant of productivity growth, as highlighted by Bessen (2019). Moreover, (ii) an increase in price competition and demand competition may generate adverse impacts on advanced economies and their employment structure. Globalization is, indeed, a multiplier of job polarization (Goos, Manning and Salomons, 2010). At last, (iii) there is a vicious circle between productivity slowdown, wage stagnation, skill obsolescence and economic growth. This last point would be explained in the following section with a formal model, known as Nelson-Phelps (1965) model of human capital.

4 Human Capital and Structural Change

In the Section 3, we have evidenced employment and wage polarization in four European countries - the stagnation of middle-skilled and middle-paid employment growth, mostly present in manufacturing, and the rise of the services' relative wages. We demonstrated that the main determinant is the inter-sectoral productivity growth differentials, known as unbalanced growth (Baumol, 1967). Moreover, as in Bárány and Siegel (2018), we have shown how less efficient workers - given their efficiency units of labor - are relocating to stagnant sectors. This dynamic could generate adverse outcomes for productivity. As long as we observe higher inter-sectoral productivity differentials and, consequently, a stronger inter-sectoral mobility of labor, there may be a reinforcing loop between productivity and labor mobility, with a depressing impact on productivity growth. Indeed, human capital is highly sector specific. Therefore, relocated workers have a lower sectoral human capital and sectoral know-how. This could lower even further productivity of the stagnant sectors, based on the view of Nelson and Phelps (1965), where human capital is essential for applying frontier technologies and generate a higher productivity growth. In turn, this may generate a reinforcing loop between lower productivity growth and higher inter-sectoral mobility of labor. As evidenced by Elstner (2018), in Germany the integration of five million low-productivity workers induced an attenuating effect on productivity growth. Indeed, this may be one of the main determinant of productivity slowdown experienced by Western economies, given the presence of structural change, inter-sectoral mobility of labor and job polarization. For explaining this vicious circle and its interactions with productivity slowdown and technological change, we are proposing a theoretical explanation, based on Nelson and Phelps (1965) and Acemoglu (2011), in order to describe the fundamental role of human capital in defining inter-sectoral productivity differentials, structural change, job polarization and technical change.

4.1 Human Capital and Technical Change

Greenwood (1999), Acemoglu (2016) and Elstner (2018) have highlighted how structural and technological change could cause a productivity slowdown through human capital. Indeed, workers need novel skills to apply efficiently a new technology to production processes. If laborers lack advanced skills to exploit new technologies, they need time to go through a process of learning-by-doing. This has already been evidenced in the introduction of the ICT and it is known as the return of the Solow paradox (Acemoglu et al., 2014). Indeed, the introduction of ICT has not implied a substantial gain in productivity, most likely because of the inability to efficiently exploit the productive power of computers and software (Acemoglu et al., 2014). Moreover, the relocation of workers from one sector to others is detrimental for workers' human capital and their acquired knowledge and know-how.

Nelson and Phelps (1965) and Acemoglu (2011) described the enhancing role of human capital in generating a higher productivity growth by applying efficiently frontier technologies. This model is fundamental for describing how structural change and inter-sector mobility of labor could adversely impact on productivity growth.

Moreover, this model is useful to clarify how structural change, employment polarization and, at the end, productivity slowdown may be linked to human capital.

4.2 Nelson-Phelps Model of Human Capital

Human capital is necessary for exploiting the productivity benefits of frontier technologies and, therefore, "to enable workers to cope with change, disruptions and especially new technologies" (Acemoglu, 2009). We use the Nelson-Phelps (1965) Model of Human Capital for explaining this intuition and the implications of the interaction between structural change and job polarization. In times of disruptive technological change, this view provides a fundamental theoretical explanation for explaining the presence of productivity slowdown, despite the adoption of productivity enhancing innovations.

Therefore, consider that the output, $Y(t)$, of an economy is given by:

$$Y(t) = A(t)L \tag{17}$$

where L is a constant labor force and $A(t)$ is the technology level of the economy. Following Acemoglu (2009), we denote the technological frontier as $A_F(t)$. This could be developed in other nations or the newest technological know-how, which has not been applied yet at the production. Moreover, $A_F(t)$ evolves exogenously as:

$$\frac{\dot{A}_F(t)}{A_F(t)} = g_F$$

with initial condition $A_F(0) > 0$. The human capital is denoted by h. As Acemoglu (2009) explains: "Human capital does not play any productivity enhancing role, but it is to facilitate the implementation and use of frontier technology in the production process". Indeed, the evolution of the technology is given by:

$$\dot{A}(t) = gA(t) + \phi(h)A_F(t) \tag{18}$$

with initial condition $A(0) \in (0, A_F(0))$. Note that g is strictly less that g_F and it measures the growth of technology $A(t)$ as a result from learning by doing and other sources of productivity growth. The second term denotes the improvements in technology because of the implementation and adoption of frontier technologies. We assume that $\phi(\cdot)$ satisfies:

$$\phi(0) = 0 \quad \text{and} \quad \phi(h) = g_F - g > 0 \quad \text{for all} \quad h \geq \bar{h}$$

where $\bar{h} > 0$. Therefore, the human capital of the workforce enables the economy to cope with new developments and frontier technologies. Indeed, if the workforce has no human capital, the adoption and implementation of frontier technologies is impossible and $A(t)$ would simply grow at the rate g. Since $A_F(t) = \exp(g_F t)A_F(0)$, the differential equation for $A(t)$ can be written as:

$$\dot{A}(t) = gA(t) + \phi(h)A_F(0)\exp(g_F t) \tag{19}$$

Therefore, solving this differential equation gives us the dynamic of the productivity growth:

$$A(t) = \left[\left(A(0) - \frac{\phi(h)A_F(0)}{g_F - g}\right)\exp(gt) + \frac{\phi(h)A_F(0)}{g_F - g}\exp(g_F t)\right] \tag{20}$$

which shows that the growth rate of $A(t)$ is faster when $\phi(h)$ is higher. In this sense, human capital is essential in applying frontier technologies to generate higher productivity growth.

4.3 Structural change, job polarization and productivity growth

We assume that human capital is not transferable between sectors and we consider a multi-sector growth model. We know from Bárány and Siegel (2018) that an inter-sectoral productivity growth differential does generate a higher inter-sectoral mobility of labor towards the stagnant sector, as proposed by Baumol (1967). This mobility could generate an even lower productivity in the stagnant sector, because of the decreasing human capital in the workforce. This could generate a higher inter-sectoral productivity differential and, therefore, a reinforcing loop. Indeed, we are now observing two different and significant phenomena: (i) frontier technology, $A_F(t)$, is growing faster even in service and this could generate a higher productivity growth, as evidenced in (20), but (ii) given the relocation of workers from the high-productive sector to the stagnant sector, the overall human capital, h, in the stagnant sector is decreasing further and this generates a lower productivity growth, $A(t)$. This is happening even if, theoretically, the introduction of novel productivity-enhancing innovations should generate stronger productivity growth. Intuitively, the relocated workers need time to learn how to apply frontier technologies, as Greenwood (1999), Acemoglu (2016) and Elstner (2018) have already pointed out.

This model could explain the reason why countries such as Italy and the United Kingdom are experiencing productivity slowdown and how other advanced economies may start to experience it. Italy and the United Kingdom may have invested less in education and human capital formation relative to France and Germany. For instance, regarding public spending on education, France and Germany are spending more than 1% of their GDP on tertiary education, while Italy and the United Kingdom are spending respectively 0.57% and 0.47% (OECD, 2018). Of course, more empirical studies are needed to find a causality between human capital investments and productivity. Nonetheless, this has not only been evidenced from Elstner (2018) for the German economy, but it has been highlighted from Visco (2017) for the Italian economy. Indeed, Visco (2017) has made it clear that "the "absolute priority for economic policy" is "strengthening human capital and investing in education".

5 Conclusion

Are machines going to substitute humans? Yes, but this will probably generate new sectors and new jobs, given stronger productivity growth, lower product prices and higher demand. What is the impact of technical change on employment and wage levels? This question is tough to answer, but something is clear. Technical change generates a stronger inter-sectoral mobility of labor and this could adversely impact on wage growth and employment levels. Bárány and Siegel (2018) showed the interaction between structural change and employment polarization in the United States, while we show that this interaction is present even in four European economies. Indeed, in this Master's thesis, we successfully calibrated the Bárány and Siegel (2018) model, using data from Germany, France, the United Kingdom and Italy. We found a shared dynamic between these countries and the U.S. and the model does well in predicting the employment shares and the wage growth patterns. Moreover, we proposed a theoretical explanation for the main determinants of productivity slowdown in the United Kingdom and Italy. This theoretical explanation is based on the model of human capital of Nelson and Phelps (1965) and it offers a clear understanding on the fundamental role of human capital for applying frontier technologies and benefit from disruptive technological change. In conclusion, productivity slowdown experienced by advanced economies in the last decades may be caused by the stronger inter-sectoral mobility of labor, employment polarization and structural change, when these processes are not accompanied by a strong human capital formation.

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6 Appendix

6.1 German abstract

In den letzten Jahrzehnten durchlebten die groen Industriestaaten einen starken Wandel in der Struktur ihrer Arbeitsmärkte. Die Polarisierung der Arbeit hatte hauptsächlich drei Gründe: Globalisierung, Routinisierung und den strukturellen Wandel. In dieser Masterarbeit untersuche ich die Dynamiken hinter der Polarisierung der Arbeit, dem Humankapital und dem strukturellen Wandel. Dafür teste ich das Model von Bàràny und Siegel (2018), ein multisektorales Wachstumsmodel, mit Daten von den bedeutendsten europäischen Lndern. In der Tat ist der strukturelle Wandel verantwortlich für die Polarisierung der Arbeit. Allerdings könnten Unterschiede im Humankapital verschiedene Produktivitäten nach sich ziehen. Daher erkläre ich wie wichtig Humankapital ist, aufbauend auf der Intuition des Models des Humankapitals von Nelson-Phelps (1965) und Baumol (1967). Diese Masterarbeit bietet eine neuartige theoretische Erklärung für die Interaktion zwischen der Polarisierung der Arbeit, dem strukturellen Wandel und dem Rückgang des Produktivitätswachstums, mit einem Schwerpunkt auf der fundamentalen Rolle des Humankapitals.