Automation and Labor Demand in European Countries: A Task-based Approach to Wage Bill Decomposition[1]

Martin LÁBAJ – Matej VITÁLOŠ***

Abstract

To understand the evolution of labor demand in European countries in the context of automation and other emerging technologies, we apply the decomposition developed by Acemoglu and Restrepo (2019) to European data. At the center of this framework is the task content of production – measuring the allocation of tasks to factors of production. By creating a displacement effect, automation shifts the task content of production against labor, while the introduction of new tasks in which labor has a comparative advantage increases the labor demand via the reinstatement effect. Contrary to the US experience, in a group of 10 European countries, the displacement effect of automation was completely counterbalanced by technologies that create new tasks in which labor has a comparative advantage. Furthermore, our cross-country comparison reveals a substantial variation across countries. The cumulative change in the task content of production ranges from 6.2% in the United Kingdom to a strong negative effect, namely –7.6%, in Sweden. A part of the differences can be explained by the rate of adoption of industrial robots. We document a strong unconditional relationship between the change in robot density and the displacement effect. However, differences in the reinstatement effect remain unexplained.

Keywords: *automation, new technologies, labor demand, displacement effect, reinstatement effect*

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* Martin LÁBAJ, University of Economics in Bratislava, Faculty of National Economy, Department of Economic Policy, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia; Institute of Economic Research SAS, Šancová 56, 811 05 Bratislava, Slovakia; e-mail: martin.labaj@euba.sk

** Matej VITÁLOŠ, University of Economics in Bratislava, Faculty of National Economy, Department of Economic Policy, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia; e-mail: matej.vitalos@euba.sk

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Introduction

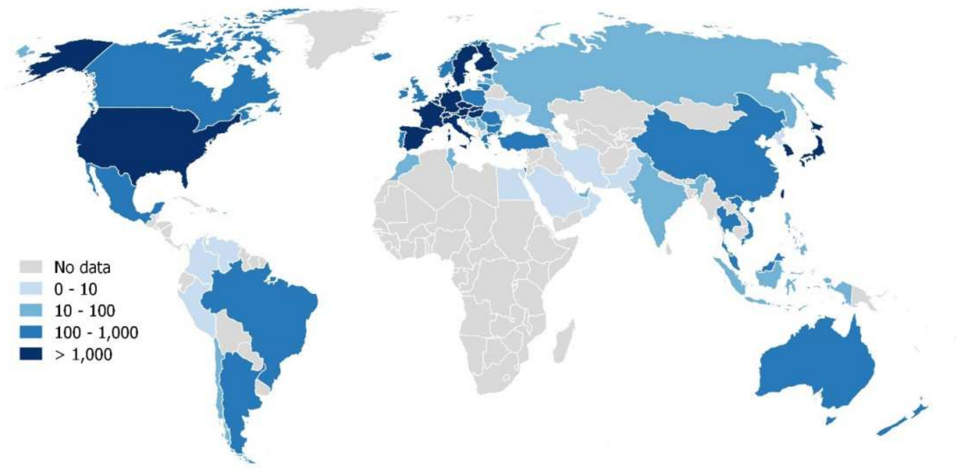
The potential disruptions associated with automation and digitization are immense. Although estimates of their impact on employment and wages vary, it is generally agreed that many professions will have to adapt to this new environment by redefining the set of tasks people currently perform to those in which they have a comparative advantage and can outperform or complement new technologies.

The speed of diffusion of digital and automation technologies – proxied by the operational stock of industrial robots – illustrates why it is important to understand the implications of these technologies. According to our calculations, worldwide operational stock of industrial robots increased from roughly 0.5 million in 1993 to more than 2 million in 2017. Moreover, in the following years, the growth of operational stock will slightly accelerate and is expected to reach an average of around 16% per year until 2021 (Litzenberger, Tsuda and Wyatt, 2018). In addition, the IDTechEx Research Report (Ghaffarzadeh, 2018), which includes market forecasts for 46 robot categories from 2018 to 2038, predicts the transformation of many industries and expects the overall market to grow significantly over the next two decades.

In 2017, 15 European countries were among the 20 countries with more than 1,000 industrial robots per million economically active persons. The remaining countries were South Korea, Taiwan, Singapore, Japan, and the United States (Figure 1).

F i g u r e 1

Number of Industrial Robots per Million Economically Active Persons (2017)



Source: Authors' elaboration based on data from the IFR and World Bank databases.

This is a significant change compared to 1993, when only Japan and Germany had more than 1,000 industrial robots per million economically active persons (Figure A1). The leading position of European countries in the implementation of industrial robots is also reflected in changes in the geographic center (centroid) of industrial robots' implementation over time. This centroid moves from its original position in Central Asia, through Europe to North America (Figure A2).

To understand the effects of automation and other types of technological changes on European labor demand, the decomposition of observed changes in the total wage bill developed by Acemoglu and Restrepo (2019) is used. It is shown that the evolution of the sources of changes in labor demand in the United States and the EU differs.

The paper is structured as follows: Section 1 includes a review of the literature on the implications of automation. Section 2 describes the decomposition of observed changes in the total wage bill developed by Acemoglu and Restrepo (2019) and explains the details of the procedure for applying this methodology to European data. Section 3 contains empirical results. It is divided into three subsections. First, a comparison between the EU and US economies is presented; then, cross-country differences are analyzed; and finally, the potential drivers of the heterogeneity across countries are discussed. The main conclusions are summarized at the end of the paper.

1. Literature Review

Over the last decade, a lot of literature on the impacts of technological change on labor market has been published. In general, it can be divided into two broad categories: i) potential future impacts, and ii) exploration of past trends. Both of them are briefly reviewed, but more space is devoted to research on past trends as this paper falls within this stream of literature.

Two different approaches are used to estimate the share of jobs that may be affected by automation or other emerging technologies in the near future. In general, the occupation-based approach developed by Frey and Osborne (2017) is associated with estimates ranging from one to two thirds of total employment being in the high-risk category (Bowles, 2014; Pajarinen and Rouvinen, 2014; Brzeski and Burk, 2015; Pajarinen, Rouvinen and Ekeland, 2015; Crowley and Doran, 2019; Michlits, Mahlberg and Haiss, 2019). Arntz, Gregory and Zierahn (2016) argue that this approach might lead to an overestimation of job automatability, as occupations labelled as those at a high risk of automation often still contain a substantial share of tasks that are hard to automate. In this way, they argue in favor of the so-called task-based approach to potential future impacts.

The task-based approach leads to significantly lower estimates, mostly around 10% (Dengler and Matthes, 2018; Pouliakas, 2018; Nedelkoska and Quintini, 2018; Mihaylov and Tijdens, 2019).

Lewney, Alexandri and Storrie (2019) extend the analysis beyond the technologically feasible substitution of workers by machines and argue that, at the microeconomic level, it is hardly the case that all that is technologically feasible will be economically rational for the firm. Moreover, from the macroeconomic perspective, the scale of investment required to replace workers with machines may just be unrealistic in terms of the share of GDP of such investment. Then there are the effects along the supply chain from the increased demand for these new technologies by firms. It must also be considered how productivity gains affect consumer demand. Because the future investment cost of automation is very uncertain, they model a high-cost case, which implies slower uptake and hence fewer direct job losses, and a low-cost case, in which uptake is faster and direct job losses are larger. The scale of job loss expected in 2030, as a proportion of the jobs projected for 2030 in a baseline scenario with no acceleration in automation, is highest in the EU – 10% in the high-cost scenario and 16% in the low-cost scenario. The corresponding numbers for the United States are 9% and 14% respectively.

Other researchers have been exploring the labor market effects of new technologies over the past few decades. Using a panel of industries from 17 countries, Graetz and Michaels (2018) show that between 1993 and 2007, robot densification (positive changes in robot density over time) increased labor productivity, total factor productivity, value added and wages. Although this first empirical analysis of the economic impact of industrial robots reveals no statistically significant effect of industrial robots on total hours worked (overall employment), there is some evidence that they reduced the hours of both low-skilled and middle-skilled workers. Carbonero, Ernst and Weber (2018) use a similar industry-country panel setting and find that between 2005 and 2014, robots led to a drop in global employment of 1.3%. The impact is rather small in developed countries, namely –0.54%, but it is much more pronounced in emerging countries, reaching around 14% – the detrimental effect of robots on employment is concentrated in emerging economies.

Contrary to this sectoral approach, Gregory, Salomons and Zierahn (2016) provide the first empirical estimate of the economy-wide effect of routine-replacing technological change (RRTC) on labor demand, assessing that RRTC has increased labor demand by up to 11.6 million jobs across Europe between 1999 and 2010, accounting for about half of total employment growth. By performing a decomposition rooted in their theoretical model, they show that sizable substitution effects of RRTC (as workers are replaced by machines in the production of routine tasks) has been overcompensated by product demand and spillover effects.

A similar central idea is behind the approach of Acemoglu and Restrepo (2020). Their model, in which robots and workers compete in the production of different tasks (task-based model), shows that greater penetration of robots into the economy affects employment and wages in two ways – negatively by directly displacing workers from tasks they were previously performing (displacement effect) and positively by increasing the demand for labor in other industries and/or tasks (productivity effect). Their model-based empirical analysis reveals large and robust negative effects of robots on employment and wages across US local labor markets – one more robot per one thousand workers reduces the employment-to-population ratio by about 0.2 percentage points and wages by 0.42%.

Dauth et al. (2017) and Chiacchio, Petropoulos and Pichler (2018) adopt this local labor market equilibrium approach and use it in the context of the EU labor market. Dauth et al. (2017) focus on Germany and find no evidence that robots have been major job killers so far. Although robots do not cause overall job losses, they do affect the composition of aggregate employment in Germany – every robot destroys roughly two manufacturing jobs.

However, over the 1994 – 2014 period, these job losses were fully offset (or even slightly over-compensated) by additional jobs in the service sector. Assessing the impact of robots on employment and wages in six EU countries (Finland, France, Germany, Italy, Spain and Sweden), Chiacchio, Petropoulos and Pichler (2018) find that one additional robot per one thousand workers reduces the employment rate by 0.16 – 0.20 percentage points – as in the case of the United States, the displacement effect dominates over the productivity effect. For the impact of industrial robots on wage growth, there are only mixed results.

Building on Acemoglu and Restrepo (2020), Acemoglu and Restrepo (2019) present a framework for understanding the effects of automation and other types of technological changes on labor demand and develop a decomposition of observed changes in the total wage bill in the economy. The displacement and productivity effects of automation are counterbalanced by the reinstatement effect, as technologies create new tasks in which labor has a comparative advantage. Their empirical decomposition shows that the deceleration of US labor demand growth over the last 30 years is a result of a combination of slow productivity growth and adverse shifts in the task contents of production – rapid automation is not being counterbalanced by the creation of new tasks.

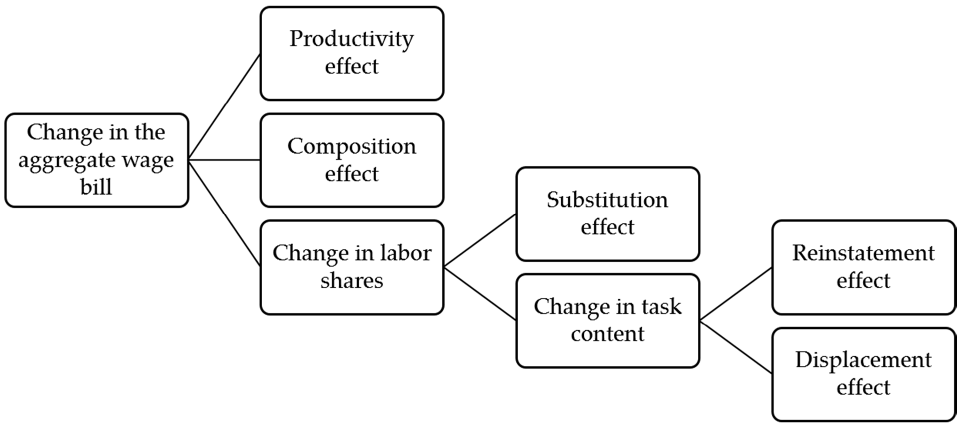
In order to study the evolution of labor demand in European countries, we apply this decomposition to European data. Although the available data covers a significantly shorter time period compared to the United States, it allows us to: (i) compare the impacts of automation and other types of technological changes on labor demand in the United States and the EU; (ii) analyze these impacts at country level; and (iii) provide the basis for further research on the causes of variation across countries and over time.

2. Methodology

2.1. Wage Bill Decomposition

Following Acemoglu and Restrepo (2019), our aim is to decompose changes in the economy-wide wage bill into the contributions of particular determinants: productivity, composition and substitution effects, and changes in the task content of production (Figure 2). The decomposition is based on a task-based framework developed to explore the effects of automation on employment, productivity and inequality.[2]

Figure 2
Wage Bill Decomposition



Source: Authors' elaboration based on Acemoglu and Restrepo (2019).

For an economy with multiple industries, aggregate wage bill captures the total amount that employers pay for labor across industries:

[2] For more details and a detailed elaboration on the relation between a task-based framework and the empirical decomposition see the original paper and its online Appendix.

$$\text{Wage bill} = \text{Value added} \times \sum_{i \in I} \text{Share of value added in industry}_i \times \text{Labor share in industry}_i$$

where time in years is indexed with the subscript t and industries with the subscript i. Because the total wage bill is the sum of wage bills across industries, the following applies:

$$\ln\left(W_t L_t\right) = \ln\left(Y_t \sum_i \chi_{i,t} s_{i,t}^L\right)$$

where

$(W_t L_t)$ – the total wage bill in year t,
Y_t – the total value added in year t,
$\chi_{i,t}$ – the share of industry i on the total value added in year t,
$s_{i,t}^L$ – the corresponding labor share.

The logarithmic form is used to decompose changes in the total wage bill over time.

If the base year is indexed with the subscript t_0, the percent change in the total wage bill normalized by population, N_t, between t_0 and t can be expressed as:

$$\begin{aligned}
\ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t_0} L_{t_0}}{N_{t_0}}\right) &= \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right) \left[\text{Productivity effect}_{t_0,t}\right] \\
&+ \ln\left(\sum_i x_{i,t} s_{i,t}^L\right) - \ln\left(\sum_i x_{i,t_0} s_{i,t}^L\right) \left[\text{Composition effect}_{t_0,t}\right] \\
&+ \ln\left(\sum_i x_{i,t_0} s_{i,t}^L\right) - \ln\left(\sum_i x_{i,t_0} s_{i,t_0}^L\right) \left[\text{Change in labor shares}_{t_0,t}\right]
\end{aligned}$$

where the first term on the right-hand side represents changes in the total value added per capita, which directly corresponds to the productivity effect. The second term on the right-hand side captures the impact of shifts in industry shares (changes in $\chi_{i,t}$ over time) on labor demand holding the labor share within each industry constant. This corresponds to the composition effect. The last term on the right-hand side captures the role of changes in labor shares within industries (changes in $s_{i,t}^L$ over time) on labor demand holding industry shares constant at their initial value. The change in labor shares corresponds to the combined effect of substitution and changes in task content. For a better understanding of the relations between these terms, we refer to Figure 2 above. It shows their schematic representation.

Acemoglu a Restrepo (2019) show that the substitution effect in industry i between t_0 and t can be computed as:

$$\text{Substitution effect}_{i,t_0,t} = (1-\sigma)\left(1-s^L_{i,t_0}\right)\left(\ln\frac{W_{i,t}}{W_{i,t_0}} - \ln\frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t}\right)$$

and the change in task content in industry i between t_0 and t as:

$$\text{Change in task content}_{i,t_0,t} = \ln s^L_{i,t} - \ln s^L_{i,t_0} - \text{Substitution effect}_{t,t_0,t}$$

where

W – denotes the price of labor (wage),
R – denotes the price of capital (rental rate),
σ – denotes the elasticity of substitution between capital and labor,
g^A – stands for the growth rate of factor-augmenting technologies.

The economy-wide contribution of the substitution effect and the economy--wide change in the task content of production are computed by aggregating across industry-level contributions of the substitution effect or changes in the task content of production. The substitution effect captures the substitution between labor- and capital-intensive tasks within an industry in response to a change in task prices. These can be caused by factor-augmenting technologies making labor or capital more productive at tasks they currently perform. Changes in the task content of production are estimated from residual changes in industry-level labor shares (beyond what can be explained by substitution effects).

Changes in the task content of production can be further decomposed into displacement and reinstatement effects. To do so, following Acemoglu and Restrepo (2019), it is assumed that in five-year windows, an industry engages in either automation or the creation of new tasks but not in both activities. This assumption implies that if the average change in the task content of production in industry i over the five-year period is negative, it is considered that the industry experiences a displacement effect. If it is positive, a reinstatement effect is assumed to take place in the industry. The total contribution of displacement and reinstatement effects can be computed by aggregating these expressions over industries and over time. Displacement effects are caused by automation that replaces labor, while reinstatement effects are driven by the creation of new tasks in which labor has a comparative advantage.

2.2. Data

The paper works with industry level data[3] for 12 European countries and the US economy. As Table 1 shows, data coverage varies across countries, and only countries with available data starting in 2000 or earlier are included in this analysis.

For the remaining European countries, the necessary data are either not available at all, or they are available only from 2008. Spain is excluded from this analysis due to missing data for eight industries (C20, C21, C26, C27, D, E, R, S).

T a b l e 1

Data Coverage by Country

Country	Years
Austria, Czech Republic, Denmark, Finland, France, Germany, Italy, Netherlands	1995 – 2017
Sweden, United Kingdom	1995 – 2016
Belgium	1999 – 2017
Slovakia	2000 – 2017
United States	1997 – 2017

Source: Authors' elaboration based on data from the EU KLEMS database.

The analysis uses data from the EU KLEMS database (2019 release). This database contains data on labor compensation, capital compensation, labor services, capital services and gross value added. For each industry and year, factor prices are calculated as:

$$W_{i,t} = \frac{\text{Labor compensation}_{i,t}}{\text{Labor services}_{i,t}}$$

$$R_{i,t} = \frac{\text{Capital compensation}_{i,t}}{\text{Capital services}_{i,t}}$$

Besides industry-level changes in effective factor prices, the substitution effect depends on the elasticity of substitution σ. Similarly to Acemoglu and Restrepo (2019), in order to estimate the substitution effect in an industry, the estimate of Oberfield and Raval (2014), $\sigma = 0.8$, was chosen as the baseline estimate of the elasticity of substitution between capital and labor. To convert observed factor prices into effective ones, it is supposed that A_i^L / A_i^K grows at a common rate equal to average labor productivity. Therefore, the average labor productivity growth for each country is calculated.

To compare the evolution of the sources of changes in labor demand in European countries and the United States, the weighted average is calculated with data for those European countries for which all the necessary data for the period 1997 – 2016 is available. This sample of European countries includes Austria,

[3] The analysis is based on data for 28 industries that are part of a market economy (A, B, C10 – C12, C13 – C15, C16 – C18, C19, C20, C21, C22_C23, C24_C25, C26, C27, C28, C29_C30, C31 – C33, D, E, F, G, H, I, J58 – J60, J61, J62_J63, K, M_N, R, S). For a robustness check, Table 6 in the Appendix compares these results with calculations based on 14 aggregated industries. The results are roughly the same.

the Czech Republic, Denmark, Finland, France, Germany, Italy, the Netherlands, Sweden, and the United Kingdom. This group of countries is referred to as EU-10. The size of each country's population is used as weights. Population data is available from the World Bank database. Given the limited availability of data described above, this sample of countries and the length of the analyzed time period is considered to be the most appropriate for the US-EU comparison. In the Appendix the results for the 12 European countries (EU-10 countries + Belgium and Slovakia) for the period 2000 – 2016 are presented, and this group of countries is referred to as EU-12.

Besides data from the EU KLEMS and World Bank databases, data on the operational stock of industrial robots from the International Federation of Robotics (IFR) is used as well. This data was used to create the map presented at the beginning of the article (Figure 1) and in the analysis of the potential drivers of cross-country heterogeneity presented in Section 3.3.

3. Empirical Results

First, the decomposition of wage bill in EU-10 (Figure 3) and the United States (Figure 4) is presented and the evolution of the sources of changes in labor demand is compared. Then, country-level results revealing the variation across countries and over time are presented. Finally, hypotheses regarding plausible determinants of cross-country differences are formulated and the potential impact of industrial robots and public policies on the displacement and reinstatement effects is discussed.

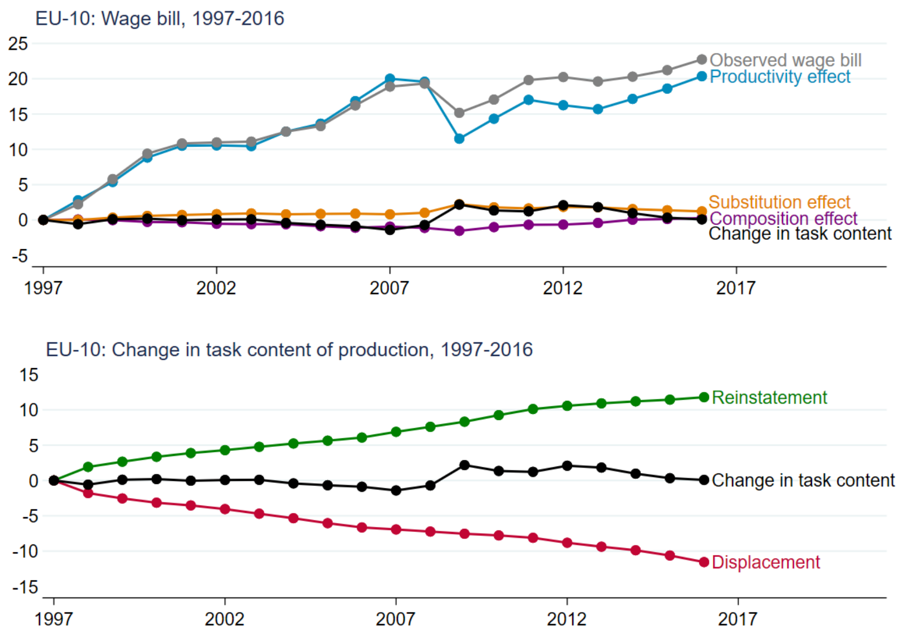
3.1. EU-US Comparison

During the 1997 – 2008 period, the evolution of the aggregate wage bill in EU-10 can be fully explained by the productivity effect. The combined effect of other sources of changes in labor was almost zero each year. The economic situation in 2009 led to a significant decline in productivity, but in the following period, labor demand and productivity grew again at almost the same pace. Although the effect of changes in the task content of production seems negligible during the entire period, it hides some fundamental changes.

The bottom panel of the Figure 3 reveals equally strong displacement and reinstatement effects. Between 1997 and 2016, the displacement effect reduced labor demand by 10.1% and the reinstatement effect increased labor demand by 9.9% – in EU-10, automation is being counterbalanced by the creation of new tasks.

Figure 3

Sources of Changes in Labor Demand (EU-10), 1997 – 2016



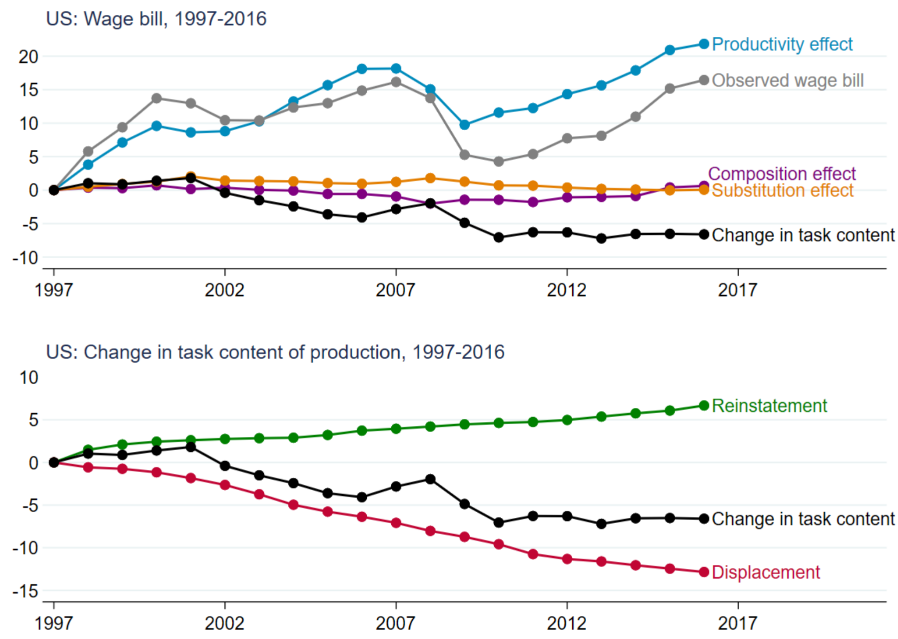
Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

While labor demand in EU-10 grew faster than could be explained by the productivity effect, the opposite is true for the US economy. Overall, Figure 3 and Figure 4 show that the growth of labor demand in the United States was slower than in EU-10. Since productivity growth in the United States was slightly faster than in EU-10 and the substitution and composition effects were weak, attention is turned to the change in the task content of production. The bottom panel of Figure 4 shows that displacement effects caused by automation were stronger than reinstatement effects driven by new tasks. Cumulatively, changes in the task content of production reduced labor demand in the US economy by 6.8% – a significant difference compared to 0.3% for EU-10. The actual reason for the slower wage bill growth in the United States is therefore a significant negative shift in the task content of production against labor between 2001 and 2006 and during the first two years since the outbreak of the 2008 financial crisis.

The comparison of the group of 10 European countries with the United States illustrates the difference in past experiences between these two major economic regions, but it hides the potential heterogeneity across European countries. Thus, they are analyzed in the next section.

F i g u r e 4

Sources of Changes in Labor Demand (United States), 1997 – 2016



Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

3.2. Cross-country Differences

Table 2 presents the sources of the cumulative change in labor demand in EU-10 countries and the United States for the 1997 – 2016 period. The table reveals substantial differences among countries. While in Italy, the observed wage bill increased by only 6.6%, in the Czech Republic it grew by almost 40%. Although most of the cross-country variation in the cumulative change in the observed wage bill can be explained by the strength of the productivity effect, changes in the task content of production played an important role in many European countries as well. The cumulative change in the task content of production ranges from a high positive effect in the United Kingdom (6.2%) to a strong negative effect in Sweden (–7.6%).

The displacement effect was stronger than the reinstatement effect in Austria, the Czech Republic, Germany, the Netherlands and Sweden. The opposite is true for Finland, France and the United Kingdom. In Denmark and Italy, the net effect was close to zero. Automation was strongest in Sweden and the Czech Republic and the creation of new tasks was strongest in the United Kingdom.

T a b l e 2

Cumulative Change in Labor Demand and Its Sources in EU-10 Countries and the United States, 1997 – 2016, in %

Country	Observed wage bill	Productivity effect	Composition effect	Substitution effect	Change in task content	Displacement effect	Reinstatement effect
Austria	24.5	24.7	2.1	0.6	**–3.6**	–12.5	8.4
Czech Republic	38.8	39.3	–2.3	1.0	**–1.6**	–18.2	14.5
Denmark	14.5	14.8	–1.9	0.6	**–0.3**	–14.3	13.8
Finland	30.1	25.1	3.0	0.0	**1.3**	–13.2	14.7
France	26.2	21.4	1.2	1.1	**2.7**	–6.2	8.5
Germany	18.4	23.4	–0.8	–0.5	**–4.7**	–14.5	10.4
Italy	6.6	1.4	0.1	2.9	**0.7**	–12.1	12.0
Netherlands	19.5	24.7	2.4	–1.2	**–6.1**	–15.7	9.3
Sweden	37.2	40.9	2.7	–0.5	**–7.6**	–18.6	10.5
United Kingdom	35.5	25.2	0.0	3.1	**6.2**	–9.1	17.1
United States	16.4	21.8	0.6	0.1	**–6.6**	–12.8	6.7

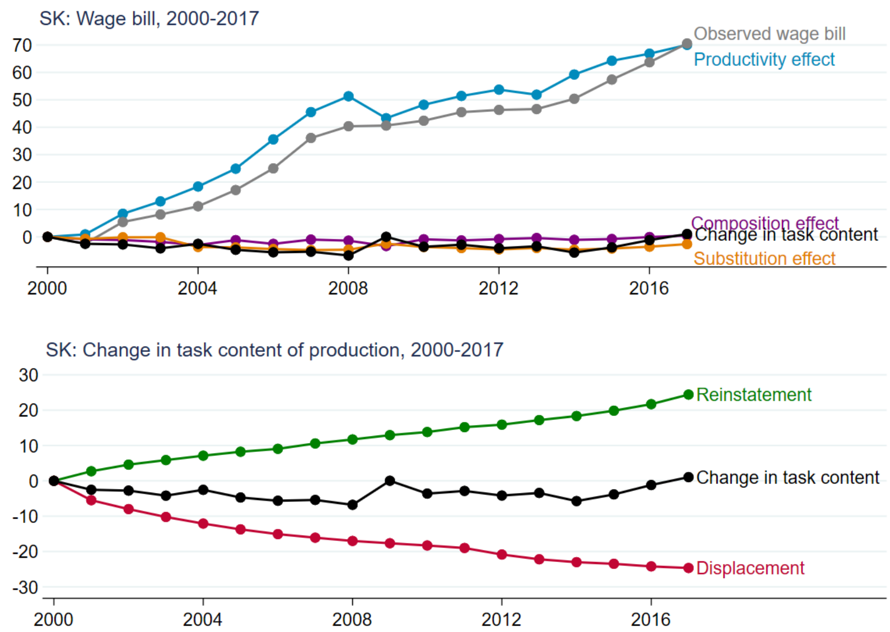
Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

A table presenting the cumulative change in labor demand and its sources for the 1995 – 2016 period can be found in the Appendix (Table 4). In this case, however, it is not possible to make a comparison between EU countries and the United States due to the limited data coverage for the United States. However, the results for EU-10 countries stay roughly the same. Due to the strong reinstatement effect at the beginning of the 1995 – 2016 period, the result for the cumulative change in the task content of production in the Czech Republic changes from –1.6% to 1.7%. The online Appendix contains figures for all countries over the longest possible periods, given the availability of data. Because of differences in base years, it is not possible to compare all pairs of countries. See Table 3 in the Appendix for a full cross-country comparison, which is available for the 2000 – 2016 period. This full cross-country comparison shows that Belgium belongs to countries in which automation strongly dominated over the creation of new tasks. Table 5 in the Appendix shows a comparison for eight European countries for the 1995 – 2017 period.

The manufacturing sector is considered a prominent user of automation technologies and a key driver of innovation. It plays an important role in the economic development in Slovakia, the Czech Republic and Germany. A comparison of the results of the wage bill decomposition among these countries reveals interesting results that call for further research.

Compared to EU-10 and the United States, the growth of labor demand in Slovakia, especially in the pre-crisis period, was much faster. This is in line with the ongoing convergence process. In Slovakia over the 2000 – 2017 period, automation was completely counterbalanced by the creation of new tasks (Figure 5).

Figure 5
Sources of Changes in Labor Demand (Slovakia)



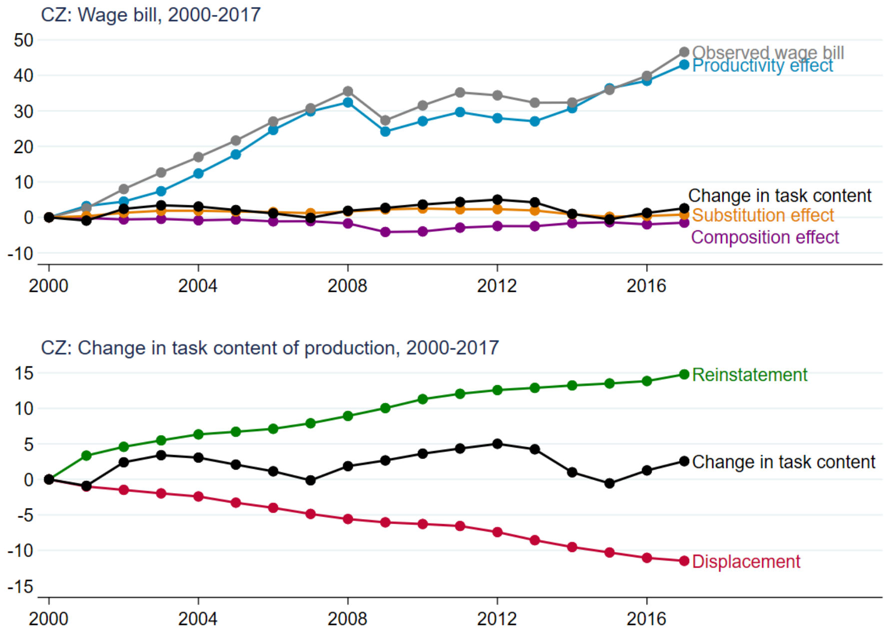
Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

Although the net effect was almost zero, there was considerable displacement and reinstatement. While the displacement effect cumulatively reduced labor demand by 24.7% during this period, the reinstatement effect increased labor demand by 24.4% during the same period. Compared to the Czech Republic (Figure 6) and Germany (Figure 13), these values can be considered relatively high. The corresponding values for the Czech Republic are 11.5% for the displacement effect and 14.8% for the reinstatement effect and for Germany 16% and 8.6% respectively.

Figure 5 also indicates a strong dominance of the creation of new tasks over automation in Slovakia during the last three years (2015 – 2017). A year later, in 2016, a similar trend began in the Czech Republic.

In the case of Germany, an opposite development can be observed – a dominance of displacement over reinstatement over the last four years. Therefore, it will be interesting to see whether these trends change or continue in the coming years.

Figure 6
Sources of Changes in Labor Demand (Czech Republic), 2000 – 2017



Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

3.3. Potential Drivers of Cross-country Heterogeneity

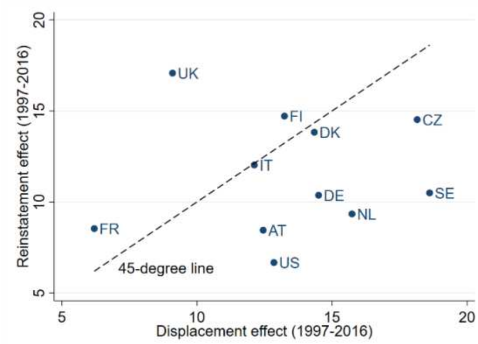
The heterogeneity identified in the previous section raises several questions. Why have European countries experienced different changes in the task content of production? Why has the reinstatement effect compensated the displacement effect in some countries but not in others? What has been the role of policies? This paper does not attempt to provide definitive answers that go beyond its scope and are the subject of further research.

An unconditional relationship between the use of industrial robots as a proxy for automation and the change in task content and the displacement and reinstatement effects can be provided. The evidence in this paper supports the hypothesis that differences in the adoption of automation technologies between European countries are strongly related to the magnitude of the displacement effect.

However, there are other potential confounding factors that could explain the identified differences, especially given the heterogeneity in the reinstatement effect. They are briefly discussed at the end of this section.

Figure 7

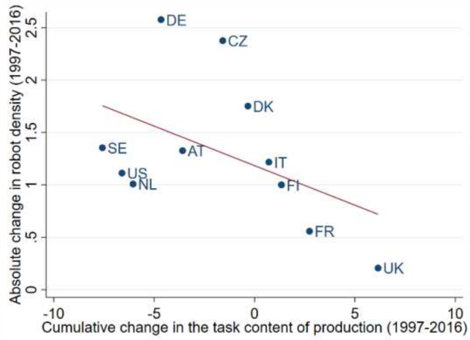
Displacement and Reinstatement Effects in EU-10 Countries and the United States



Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

Figure 8

Change in Robot Density versus the Change in Task Content



Note: Robot density refers to the stock of industrial robots per one thousand workers.

Source: Authors' elaboration based on data from the EU KLEMS, World Bank and IFR databases.

Figure 7 provides a different form of presentation of the results, which are discussed in more detail in the previous section. Countries below the 45-degree line experienced a negative shift in the task content of production and countries above the line experienced a positive shift in the task content of production. The farther the country from the line, the stronger the dominance of one effect over another. The displacement effect was strongly dominant in the United States, the Netherlands and Sweden. Reinstatement dominated in the United Kingdom. There are no clear clusters of countries that could be identified from this figure.

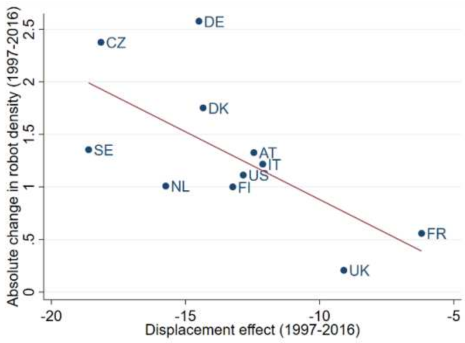
To get more insight into the potential drivers of heterogeneity across countries, the measured effects are related with the adoption of industrial robots.

Figure 8 shows that countries where the increase in robot density was stronger between 1997 and 2016 experienced a more significant negative shift in the task content of production.

Figure 9 documents a strong negative association between the displacement effect and the change in robot density. While in the Czech Republic and Germany, where the increase in robot density was strongest, automation reduced labor demand by 18.2 and 14.5%, respectively, in the United Kingdom and France, where the increase in robot density was weakest, automation reduced labor demand by only 9.1 and 6.2%, respectively. This is in line with both intuition and the definition of automation technologies. At the same time, it supports the decomposition derived by Acemoglu and Restrepo (2019) and provides evidence that the displacement of human labor associated with automation technologies is really measured.

F i g u r e 9

Change in Robot Density versus the Displacement Effect

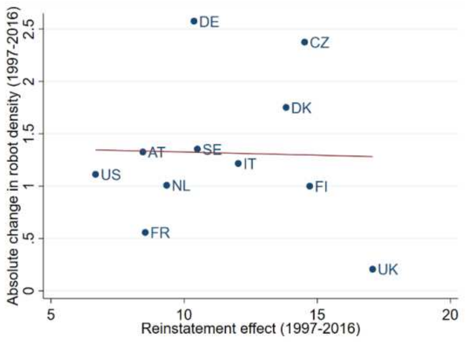


Note: Robot density refers to the stock of industrial robots per one thousand workers.

Source: Authors' elaboration based on data from the EU KLEMS, World Bank and IFR databases.

F i g u r e 10

Change in Robot Density versus the Reinstatement Effect



Note: Robot density refers to the stock of industrial robots per one thousand workers.

Source: Authors' elaboration based on data from the EU KLEMS, World Bank and IFR databases.

As expected, there is no relationship between the change in robot density and the reinstatement effect – the implementation of industrial robots does not seem to be associated with the creation of new tasks (Figure 10). There is no clear reason to automatically find an association between the adoption of automation technologies and the creation of new tasks. At the same time, it motivates further exploration of the drivers of reinstatement effects. Why do countries with a similarly strong displacement effect and a similar change in the adoption of industrial robots (e.g. the United States and Finland) differ so much in the reinstatement effect?

It is natural to think of institutions and policies as drivers of these differences. Several hypotheses could be tested and explored in further research (confounding factors in the case of the US economy and limitations of the model are discussed in Acemoglu and Restrepo, 2019). Countries differ in their industrial policies and support of automation. Strong government incentives for automation can lead to inefficiently high levels of worker displacements without creating productivity gains and new job opportunities. Differences in tax code, and in particular high taxes on labor, can be harmful to the creation of new labor tasks. One of the limitations of the model is that it assumes competitive labor markets. However, the existence of collective bargaining, differences in labor codes and the power of labor unions can explain part of the differences between countries. Structure of the economy and potential mismatch between the skills of the labor force and the adoption of automation technologies can increase the gap between the displacement and reinstatement effects as well. These and other drivers should be investigated in further research.

Conclusions

Automation and other new technologies raise questions about their potential labor market impacts and the future of employment. To successfully overcome upcoming challenges and to avoid wrong decisions, an understanding of past trends is necessary.

To understand the evolution of labor demand in European countries, the decomposition developed by Acemoglu and Restrepo (2019) was applied to European data. This allowed for comparing the evolution of the sources of labor demand growth in the EU and the United States and across European countries.

On average, EU countries have experienced different trends from the United States. Contrary to the US experience, in EU-10 between 1997 and 2016, the displacement effect of automation was completely counterbalanced by technologies that create new tasks in which labor has a comparative advantage. Furthermore, the cross-country comparison in this paper reveals a substantial variation across countries. The displacement effect was stronger than the reinstatement effect in Austria, the Czech Republic, Germany, the Netherlands and Sweden. The opposite was true for Finland, France and the United Kingdom. In Denmark and Italy, the net effect was close to zero. Automation was strongest in Sweden and the Czech Republic and the creation of new tasks was strongest in the United Kingdom.

Since there does not seem to be a clear line between countries that have experienced either a positive or a negative shift in the task content of production, this calls for further empirical exploration. This paper provided empirical evidence on the relationship between the adoption of industrial robots (as a proxy for automation) and the change in the task content of production. The negative association between them is driven by the displacement effect – there is a strong association between the displacement effect and the change in robot density. However, differences in the reinstatement effect remain unexplained. A few potential factors closely related to policies and institutions that could explain them and are open for further research were discussed. A better understanding of the determinants of the identified variation may help policymakers to take the right measures to benefit from ongoing technological changes.

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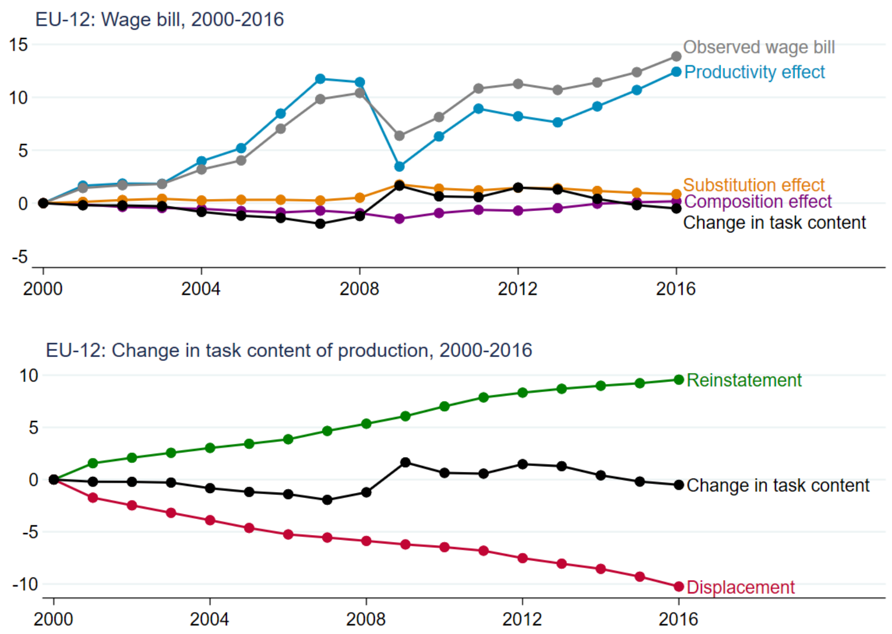
Appendix

Figure 11

Sources of Changes in Labor Demand (EU-12)



Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

Table 3

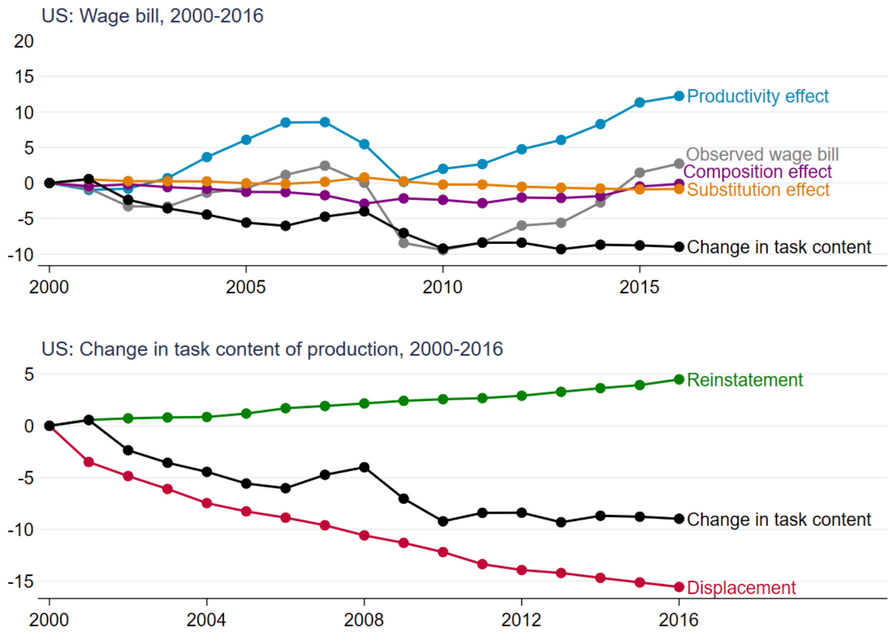
Cumulative Change in Labor Demand and Its Sources in EU-12 Countries and the United States, 2000 – 2016, in %

Country	Observed wage bill	Productivity effect	Composition effect	Substitution effect	Change in task content	Displacement effect	Reinstatement effect
Austria	14.6	13.8	1.5	1.0	**–2.4**	–10.7	7.4
Belgium	8.9	15.5	0.7	–1.6	**–6.3**	–13.3	6.9
Czech Republic	39.9	38.5	–2.0	0.6	**1.1**	–12.1	13.7
Denmark	5.7	5.3	–0.5	0.5	**–1.0**	–11.3	10.8
Finland	20.6	12.0	4.2	1.0	**2.5**	–12.0	14.6
France	16.7	8.9	0.9	1.7	**4.5**	–4.1	8.8
Germany	11.1	17.8	–0.7	–1.0	**–6.0**	–14.9	8.4
Italy	3.1	–6.2	0.2	3.7	**4.7**	–7.0	12.5
Netherlands	6.4	12.0	1.1	–1.2	**–6.0**	–14.0	7.3
Slovakia	63.7	66.8	–0.1	–3.8	**–1.0**	–24.7	21.7
Sweden	25.1	27.6	1.6	0.1	**–5.5**	–15.3	9.5
United Kingdom	17.2	15.5	–0.2	1.2	**–0.5**	–9.7	8.4
United States	2.7	12.2	–0.1	–0.8	**–9.0**	–15.6	4.5

Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

F i g u r e 12

Sources of Changes in Labor Demand (United States), 2000 – 2016



Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

T a b l e 4

Cumulative Change in Labor Demand and Its Sources in EU-10 Countries, 1995 – 2016, in %

Country	**Observed wage bill**	**Productivity effect**	**Composition effect**	**Substitution effect**	**Change in task content**	**Displacement effect**	**Reinstatement effect**
Austria	27.9	29.2	2.6	0.1	**–5.0**	–15.0	9.1
Czech Republic	44.6	39.7	–2.8	3.4	**1.7**	–17.8	19.2
Denmark	16.8	17.8	–2.4	0.3	**0.0**	–15.3	15.0
Finland	39.5	35.3	3.7	–0.7	**0.3**	–15.3	15.1
France	28.0	24.3	1.1	0.8	**2.3**	–7.0	8.8
Germany	17.6	24.5	–1.2	–0.6	**–5.7**	–16.6	10.6
Italy	9.6	4.6	0.1	2.8	**0.7**	–12.6	13.0
Netherlands	25.7	32.5	3.1	–1.6	**–8.0**	–19.1	9.7
Sweden	43.7	45.2	1.9	0.2	**–5.2**	–17.4	12.4
United Kingdom	38.4	30.8	0.3	2.5	**3.3**	–13.1	15.7

Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

Table 5

Cumulative Change in Labor Demand and Its Sources in Eight EU Countries, 1995 – 2017, in %

Country	Observed wage bill	Productivity effect	Composition effect	Substitution effect	Change in task content	Displacement effect	Reinstatement effect
Austria	29.7	31.7	2.8	0.3	**–5.9**	–15.4	8.9
Czech Republic	51.3	44.3	–2.0	3.6	**3.1**	–17.1	20.3
Denmark	18.0	19.7	–0.6	–0.2	**–1.5**	–16.2	15.0
Finland	38.9	39.3	4.2	–1.6	**–3.9**	–18.6	14.7
France	31.1	26.8	1.2	1.1	**2.7**	–7.3	9.4
Germany	19.4	26.7	–0.7	–0.6	**–7.0**	–17.9	10.8
Italy	10.9	6.7	0.3	2.6	**–0.1**	–13.3	13.0
Netherlands	27.6	34.9	3.5	–1.5	**–9.1**	–20.5	9.8

Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

Table 6

Change in the Task Content of Production and Displacement and Reinstatement Effects in EU-10 Countries and the United States – 28 versus 14 Industries (1997 – 2016)

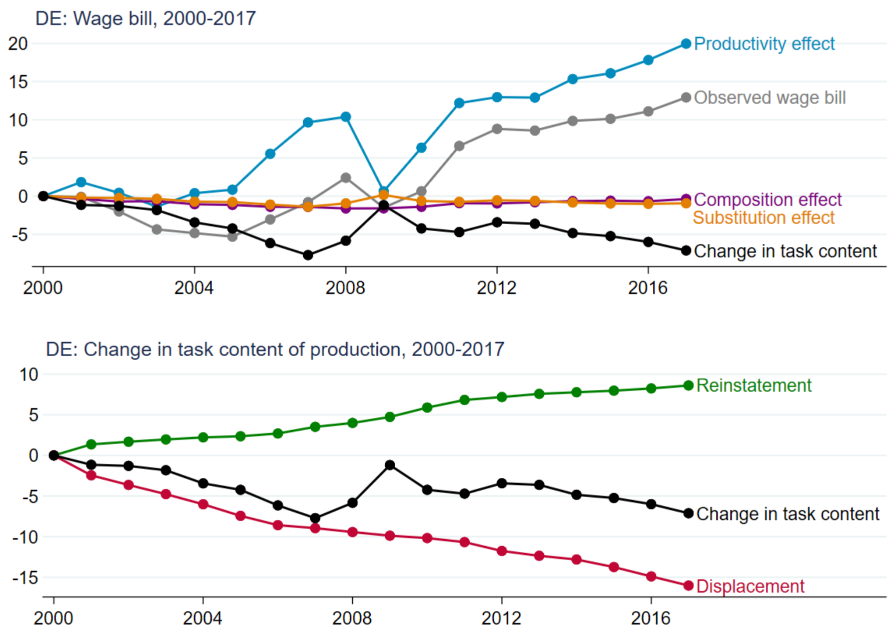
Country	28 industries			14 industries		
	Change in task content	Displacement effect	Reinstatement effect	Change in task content	Displacement effect	Reinstatement effect
Austria	**–3.6**	–12.5	8.4	**–2.8**	–10.4	7.3
Czech Republic	**–1.6**	–18.2	14.5	**–1.2**	–14.8	11.5
Denmark	**–0.3**	–14.3	13.8	**–2.9**	–15.0	12.1
Finland	**1.3**	–13.2	14.7	**2.0**	–10.9	12.6
France	**2.7**	–6.2	8.5	**3.2**	–5.3	8.1
Germany	**–4.7**	–14.5	10.4	**–4.4**	–12.4	8.6
Italy	**0.7**	–12.1	12.0	**1.1**	–11.1	11.5
Netherlands	**–6.1**	–15.7	9.3	**–5.7**	–14.0	8.1
Sweden	**–7.6**	–18.6	10.5	**–5.8**	–14.6	7.9
United Kingdom	**6.2**	–9.1	17.1	**6.4**	–7.7	15.9
United States	**–6.6**	–12.8	6.7	**–6.9**	–12.7	6.2

Note: 28 industries: A, B, C10-C12, C13-C15, C16-C18, C19, C20, C21, C22_C23, C24_C25, C26, C27, C28, C29_C30, C31-C33, D, E, F, G, H, I, J58-J60, J61, J62_J63, K, M_N, R, S;14 industries: A, B, C, D, E, F, G, H, I, J, K, M_N, R, S.

Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

F i g u r e 13

Sources of Changes in Labor Demand (Germany), 2000 – 2017



Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.