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Automation and labor demand in European countries: A task-based approach to wage bill decomposition*

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Abstract

To understand the effects of automation and other types of technological changes on European labor demand, we use an empirical decomposition of observed changes in the total wage bill in the economy developed by Acemoglu and Restrepo (2019). The decomposition is derived from a task-based model that allows us to study the effects of different technologies on labor demand. At the center of this framework is the task content of production—measuring the allocation of tasks to factors of production. Automation, by creating a displacement effect, shifts the task content of production against labor, while the introduction of new tasks in which labor has a comparative advantage improves it via the reinstatement effect. Overall effects are country- and time-specific and call for an empirical exploration. We apply the decomposition to 15 European countries with good data coverage in the EU KLEMS database.

Keywords: automation, displacement effect, labor demand, productivity, reinstatement effect, technology, wage share

JEL Codes: J23, J24

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1 Introduction

There are at least two relevant reasons for analyzing the economic and social implications of automation, especially in European countries.

Firstly, worldwide operational stock of industrial robots increased from roughly 0.5 million in 1993 to more than 2 million in 2017 (Table 1). Moreover, in the following years, growth of operational stock will slightly accelerate and is expected to be around 16% on average per year until 2021 (Figure 4). In addition, the IDTechEx report, which includes market forecasts for 46 robot categories from 2018 to 2038 (Figure 5), predicts the transformation of many industries and expects the overall market to grow significantly over the next two decades.

Secondly, in 2017, up to 15 European countries were among 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 6 and Table 2). 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 7). The leading position of European countries in the implementation of industrial robots is also reflected in changes in the geographic centre (centroid) of industrial robots implementation over time. This centroid moves from its original position in Central Asia, through Europe to North America (Figure 8).

To understand the effects of automation and other types of technological changes on European labor demand, we use an empirical decomposition of observed changes in the total wage bill in the economy developed by Acemoglu and Restrepo (2019). We identify the variability in the evolution of the sources of changes in labor demand among European countries and over time, and considerable differences between the group of European countries (EU-12) and the US. Therefore, further research will be necessary in order to understand more fundamental determinants of this variation.

2 Literature review

In recent years, many researchers have begun to focus on the economic and social implications of automation and other forms of technological advancement. Considering the historical experience with significant technological advances (Mokyr et al. (2015)), potential and actual labor market disruptions seem to be the most obvious and natural research objective.

2.1 Future of employment

As already mentioned, one branch of this particular literature tries to estimate the share of jobs that will be potentially replaced by robots in the near future. These studies differ in the approaches used—the two basic approaches are an occupation-based approach and a task-based approach.

Those who use an occupation-based approach come with estimates that in some countries almost two-thirds of jobs are at high risk of automation (Bowles (2014), Pajarinen et al. (2014), Brzeski and Burk (2015), Pajarinen et al. (2015), Frey and Osborne (2017), Crowley and Doran (2019), Michlits et al. (2019)). All these studies use estimates of the probability of automation for 702 occupations of Frey and Osborne (2017). By taking into account a wide set of individual characteristics, such as socio-demographic characteristics, human capital variables, and the region of residence, the micro-level approach of Fossen and Sorgner (2018) verify the relevance of these estimates. An analysis of individual-level labor market transitions shows that those whose jobs are more at risk of automation are more likely to become unemployed than those less threatened by automation and that occupations with a higher risk of automation are associated with more frequent job changes.

Arntz et al. (2016) argue that this approach might lead to an overestimation of job automatibility, as occupations labelled as those at high risk of automation often still contain a substantial share of tasks that are hard to automate. Using a task-based approach, their corresponding estimates range from 2 to 12%.

Other researchers use either a combination of these two approaches or their own methodology to come up with their own corresponding estimates (Manyika (2017), Hawksworth et al. (2018), Nedelkoska and Quintini (2018), Muro et al. (2019)). Their estimates range from 22 to 56%, so they are closer to the estimates of authors using an occupation-based approach than to those of Arntz et al. (2016).

Lewney et al. (2019) extend the analysis beyond just the technologically feasible substitution of workers by machines by incorporating some economics into the analysis. They 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. There are also the effects along the supply chain from the increased demand for these new technologies by firms. However, the most important issue is how the 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, 16% in the low-cost scenario). The corresponding numbers for the US are 9 and 14%.

2.2 Role of automation in past and ongoing labor market changes

Another branch of this particular literature seeks to assess the role of automation in labor marker changes over the past few decades.

In a pioneering study empirically analyzing the economic impacts of automation technologies, namely industrial robots, using a panel of industries from 17 countries, Graetz and Michaels (2018) conclude that in addition to its positive effects on labor productivity and value added – thus contributing substantially to economic growth, this technology increased both total factor productivity and wages and had no significant effect on overall employment during 1993-2007. However, there is some evidence that robot densification crowds out employment of low-skilled and, to a lesser extent, middle-skilled workers.

Contrary to this sectoral approach, Gregory et al. (2016) provide the first estimate of the economy-wide effect of routine-replacing technological change (RRTC) on labor demand, assessing that it has increased labor demand by up to 11.6 million jobs across Europe in 1999-2010—total employment increased by 23 million jobs over the same period. The decomposition shows that RRTC has decreased labor demand by 9.6 million jobs as capital replaces labor in production. However, this has been overcompensated by product demand and spillover effects which have together increased labor demand by some 21 million jobs. These results indicate that when assessing the labor market effects of technological change, it is also important to take into account product demand and its associated spillovers.

Similar conclusions are formulated by Vermeulen et al. (2018), who unite an evolutionary economic model of multisectoral structural change with labor economic theory to provide a comprehensive framework of how displacement of labor in sectors of application (sectors in which automation technology is applied) is compensated by intra- and intersectoral countervailing effect. While their expert-based estimation of the automatability of jobs in the applying sectors is limited, the shifts of employment to the "making" sectors (sectors of production, development, supply and support of automation technology) is salient—there is substantial job creation in "making" sectors as well as in complementary facilitating and inhibiting sectors, both in existing and emerging occupations. Aggregating over changes in the sectoral composition of the economy and projected employment in the various sectors, there is support for the "rebound" scenario—the job loss in the applying sectors is limited, while the potential for job creation is substantial, both in directly related (new) sectors as well as in the spillover sectors. Therefore, the authors prefer the term "usual structural change" to "end of work".

In contrast to these results, using a model in which industrial robots compete against human labor in the production of different tasks, Acemoglu and Restrepo (2017) estimate that one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5% and show that the US local labor market effects can be estimated by regressing the change in employment and wages on the exposure to robots in each local labor market. The central idea behind this approach is that technological innovations and greater penetration of robots into the economy affect 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). Although the authors rely on the same data as Graetz and Michaels (2018), they use a different empirical strategy, which enables them to go beyond cross-country, cross-industry comparisons and exploit plausibly exogenous changes in the spread of robots. Moreover, microdata enables them to control for detailed demographic and compositional variables.

Dauth et al. (2017) focus on Germany and use a similar local labor market approach as Acemoglu and Restrepo (2017) to find no evidence that robots have been major job killers so far. Robots do not cause overall job losses, but they do affect the composition of aggregate employment in Germany. They estimate that every robot destroys roughly two manufacturing jobs. This implies a total loss of 275 000 manufacturing jobs over the period 1994-2014. However, this loss was fully offset (or even slightly over-compensated) by additional jobs in the service sector.

Based on the employment reduction coefficients estimated by Acemoglu and Restrepo (2017), further research comes with further estimates of the actual decline in employment due to automation.

Carbonero et al. (2018) find that robots have led to a drop in global employment of 1.3% between 2005 and 2014. The impact is rather small in developed countries, -0.54%, but much more pronounced in emerging countries with about 14%—the detrimental effect of robots on employment is concentrated in emerging economies, taking place both within countries and through the global supply chain.

In the case of European countries, Chiacchio et al. (2018) find more modest impact of robots on employment rate and statistically insignificant impact on wages. In a sample of six countries (Finland, France, Germany, Italy, Spain and Sweden), the introduction of robots into production processes reduces employment rates—one additional robot per thousand workers reduces the employment rate by 0.16-0.20 percentage points. Thus, as in the case of the United States, the displacement effect dominates over the productivity effect.

Building on Acemoglu and Restrepo (2017) using data on 28 industries for 18 OECD countries since 1970, Salomons et al. (2018) empirically estimate the employment and labor share impacts of productivity growth—an omnibus measure of technological change. Although automation (whether measured by total factor productivity growth or instrumented by foreign patent flows or robot adoption) has not been employment-displacing, it has reduced labor's share in value-added. These labor share-displacing effects of productivity growth, which were essentially absent in the 1970s, have become more pronounced over time, and are most substantial in the 2000s—in recent decades, automation has become less labor-augmenting and more labor-displacing.

Like Gregory et al. (2016), Acemoglu and Restrepo (2019) explore the effects of automation and other types of technological changes on labor demand. They present a framework for understanding the effects of automation and other types of technological changes on labor demand, and use it to interpret changes in US employment over the recent past. The central idea is as follows. Production requires tasks which are allocated to labor or capital. New technologies impact this allocation, leading to changes in the task content of production. Automation enables capital to replace labor in tasks it was previously engaged in, thereby shifting the task content of production against labor—automation always reduces the labor share in value added and may reduce labor demand even as it raises productivity (the aforementioned displacement effect). This occurs when automation technology is only marginally better than the replaced workers—a combination of sizable workforce replacement and modest productivity growth. By allowing a more flexible allocation of tasks to factors of production, automation technology truly increases productivity and contributes to the demand for labor in non-automated tasks, but the presumption that all technologies increase (aggregate) labor demand simply because they raise productivity is wrong. As demonstrated by a simple task-based model in Acemoglu and Restrepo (2017), robots may indeed have both a positive or a negative effect on employment and wages, with their positive impact resulting from the productivity effect, while their negative impact is due to the direct displacement of workers by robots. However, this disrupting effect of automation is counterbalanced by the creation of new tasks in which labor has a comparative advantage—automation always raises the labor share and labor demand (reinstatement effect). The authors use this framework to analyze the evolution of the labor demand in the United States since World War II. The sharp slowdown of US wage bill growth over the last three decades is a consequence of weak productivity growth and significant shifts in the task content of production against labor. Considerably stronger displacement effects than reinstatement effects during the last 30 years compared to decades before suggest an acceleration of automation and a deceleration in the creation of new tasks.

Hicks and Devaraj (2015) breaks down changes in US manufacturing employment into three factors: productivity, trade, and domestic demand. According to their findings, almost 88% of job losses in US manufacturing in recent years can be attributable to productivity growth, while trade (net exports) has contributed only to roughly 13.4% of job losses. On the other hand, growing demand for manufacturing goods in the US has offset some of those job losses, but the effect is modest, accounting for a 1.2% increase in jobs.

3 Methodology

Our aim is to decompose changes in the economy-wide wage bill into contributions of particular determinants—productivity, composition and substitution effects, and changes in task content of production (Figure 1). Changes in task content of production are related to technological progress. The decomposition was proposed by Acemoglu and Restrepo (2019). It is based on a task-based framework developed to explore the effects of automation on employment, productivity and inequality.[1]

Wage bill captures the total amount employers pay for labor, and thus

$$\text{Wage bill} = \text{Value added} \times \text{Labor share.}$$

For an economy with multiple industries:

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

We index time in years with the subscript t and industries with the subscript i. Because the total wage bill is the sum of wage bills across industries, we have:

$$\ln(W_t L_t) = \ln \left(Y_t \sum_i \chi_{i,t} s^L_{i,t} \right), \tag{1}$$

where $(W_t L_t)$ is the total wage bill in year t, Y_t is total value added in year t, $\chi_{i,t}$ is the share of industry i's in total value added in year t, and $s^L_{i,t}$ is the corresponding labor share. Logarithmic form is used to decompose changes in the total wage bill over time.

If we index the base year with the subscript t_0, we can express the percent change in

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

Figure 1: Wage bill decomposition

Change in the aggregate wage bill

- Productivity effect
- Composition effect
- Change in labor shares
  - Substitution effect
  - Change in task content
    - Reinstatement effect
    - Displacement effect

the total wage bill normalized by population, N_t, between t_0 and t as

$$\begin{aligned}
\ln\left(\frac{W_tL_t}{N_t}\right) - \ln\left(\frac{W_{t_0}L_{t_0}}{N_{t_0}}\right) = \quad & \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right) [\text{ Productivity effect}_{t_0,t}] \\
& + \ln\left(\sum_i \chi_{i,t} s^L_{i,t}\right) - \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t}\right) [\text{ Composition effect}_{t_0,t}] \\
& + \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t}\right) - \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t_0}\right) [\text{ Change in labor shares}_{t_0,t}],
\end{aligned} \tag{2}$$

where the first term on the right-hand side represents changes in 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 $s^L_{i,t}$ 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.

Acemoglu and Restrepo (2019) show that we can compute the substitution effect in an industry i between t_0 and t as

$$\text{Substitution effect}_{i,t_0,t} = (1-\sigma)(1-s^L_{i,t_0})\left(\ln\frac{W_{i,t}}{W_{i,t_0}} - \ln\frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t}\right) \tag{3}$$

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

$$\text{Change in task content}_{i,t_0,t} = \ln s^L_{i,t} - \ln s^L_{i,t_0} - \text{Substitution effect}_{i,t_0,t}, \tag{4}$$

where W denotes the price of labor (the wage), R denotes the price of capital (the rental rate), σ denotes the elasticity of substitution between capital and labor, and 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 task content. 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. The change in task content of production is estimated from residual changes in industry-level labor shares (beyond what can be explained by substitution effects).

We can further decompose changes in task content into displacement and reinstatement effects. To do so, we assume, that over five-year windows, an industry engages in either automation or the creation of new tasks but not in both activities. This assumption implies that

$$\text{Displacement}_{i,t-1,t} = \min\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} \text{Change in task content}_{i,\tau-1,\tau}\right\} \tag{5}$$

$$\text{Reinstatement}_{i,t-1,t} = \max\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} \text{Change in task content}_{i,\tau-1,\tau}\right\}. \tag{6}$$

We can compute the total contribution of displacement and reinstatement effects by aggregating these expressions over industries i and over time t_0 and t. Displacement effects are caused by automation that replaces labor, while reinstatement effects are driven by creation of new tasks in which labor has a comparative advantage.

4 Data

We use data available on the EU KLEMS website.[2] Basic Files contain data on labor and capital compensation (in millions of national currency), labor and capital services (volume indices) and gross value added, both at current basic prices (in millions of national currency) and volumes. For each industry and year, we calculate factor prices as

$$W_{i,t} = \frac{\text{Labor compensation}_{i,t}}{\text{Labor services}_{i,t}} \tag{7}$$

$$R_{i,t} = \frac{\text{Capital compensation}_{i,t}}{\text{Capital services}_{i,t}}. \tag{8}$$

Besides industry-level changes in effective factor prices, the substitution effect depends on the elasticity of substitution σ. As Acemoglu and Restrepo (2019), in order to estimate the substitution effect in an industry, we choose as our baseline estimate of the elasticity of substitution between capital and labor the estimate of Oberfield and Raval (2014), $\sigma = 0.8$. To convert observed factor prices into effective ones, we suppose that A_i^L/A_i^K grows at a common rate equal to average labor productivity, which we take to be 1.46% (Acemoglu and Restrepo (2019)).

We work with data for 16 countries and 13 industries. From the available number of 19 industries, we exclude those that are not part of the market economy (Table 3). Also, not for every country we have all the necessary data for the same period of time (Table 4).

In order to compare the evolution of the sources of changes in labor demand in European countries and the US, we calculate the weighted average with data for those European

[2]September 2017 release, Revised July 2018

countries for which we have all the necessary data for the period 2000-2014. This sample of European countries includes Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Italy, Netherlands, Sweden, and United Kingdom. We refer to this group of countries as EU-12. As weights we use the size of each country's population.

5 Results

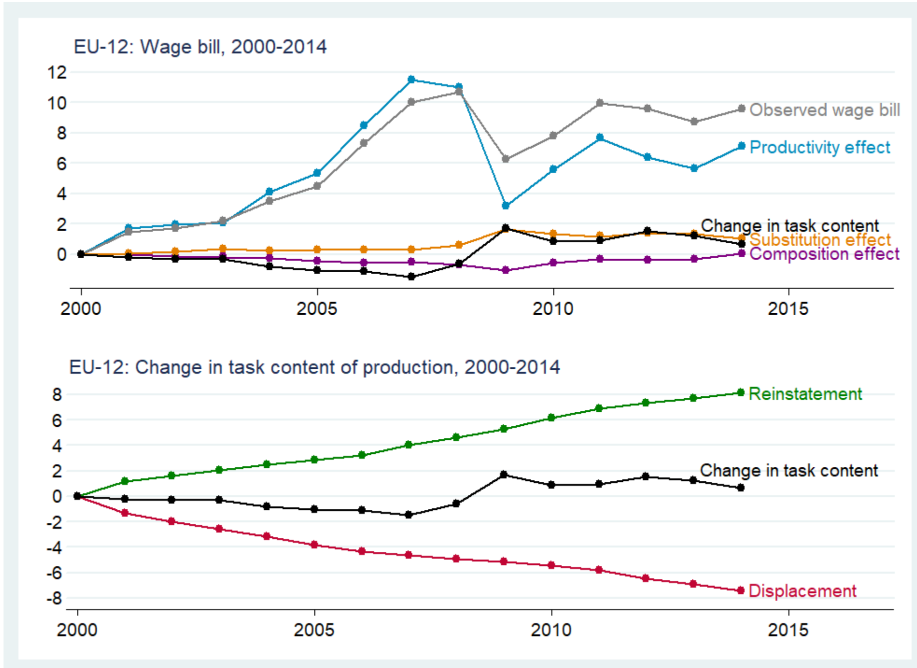
Over the periods analysed, as in the US (Figure 24), dominating displacement effect reduced labor demand in Austria (Figure 9), Belgium (Figure 10), Czechia (Figure 11), Germany (Figure 12), Denmark (Figure 13), Spain (Figure 14), Luxembourg (Figure 18), Netherlands (Figure 19), Sweden (Figure 20) and Slovakia (Figure 22). This reduction was most pronounced in Belgium, followed by Germany and Spain. In the case of Spain, this reduction occurred only during the last years of the period analysed (2011-2015). Special cases are Czechia and Slovakia. Cumulatively, changes in task content reduced labor demand in these two countries, but this reduction was only negligible and these changes were relatively small throughout the periods analysed.

Contrary to these results, in Finland (Figure 15), France (Figure 16), Italy (Figure 17), Slovenia (Figure 21) and the UK (Figure 23), automation increased labor demand rather than decreased. This increase was most pronounced in the UK, but all the positive changes occurred at the very beginning of the period analysed (1997-2001).

There are also differences between countries in periods when one effect prevails over another. In Austria, Finland and France, in 2007, after a long period of negative changes in task content, the reinstatement effect began to dominate. In the case of Italy, this reversal occurred earlier, in 2001. In contrast to these results, the opposite happened in Denmark and Spain. In Denmark, in 2009, after a long period of positive changes in task content of production, the displacement effect began to dominate.

Although changes in task content were less pronounced in European countries than

Figure 2: Sources of changes in labor demand (EU-12)

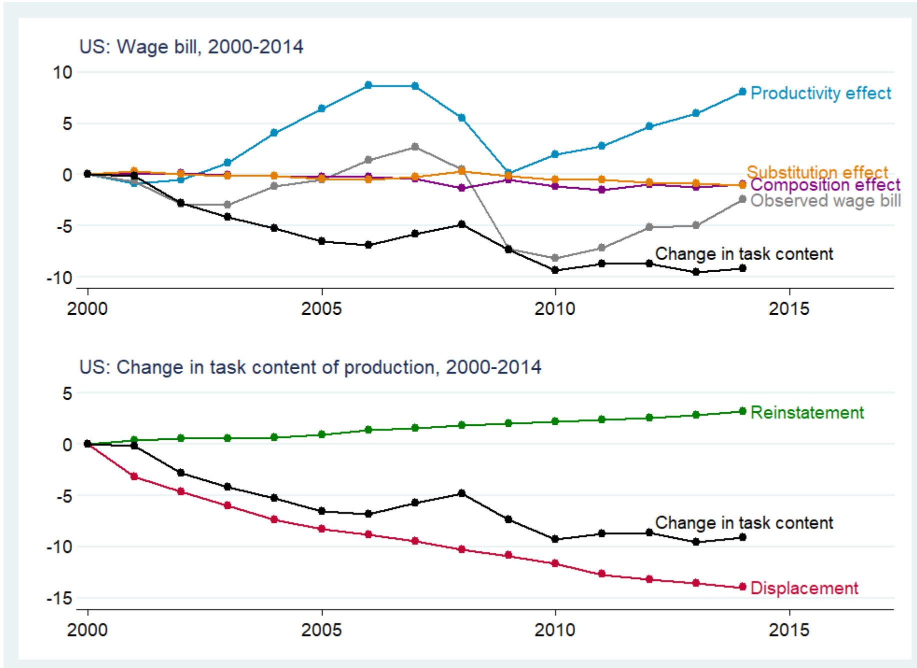


Note: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Italy, Netherlands, Sweden, United Kingdom. Weighted average.

in the US, there was considerable displacement and reinstatement. Our findings therefore indicate that there was a lot of automation in European countries. Automation was most pronounced in Slovakia, where between 2004 and 2015 displacement effect reduced labor demand by 14.9%, while reinstatement effect simultaneously increased labor demand by 11.7%. Automation was the least significant in France, where between 1995 and 2015 the displacement effect reduced labor demand by 6.0%, while the reinstatement effect simultaneously increased labor demand by 8.1%.

When comparing the evolution of the change in task content of production between the EU-12 and the US, we find that while in the US labor demand was reduced by dominating displacement effect, in the EU-12 happened exactly the opposite—although negligibly, but automation increased labor demand rather than decreased (Figures 2 and 3). These negative changes in task content, coupled with slow productivity growth, resulted in lower observed wage bill in the US in 2014 than in the base year (2000). In contrast, positive changes in

Figure 3: Sources of changes in labor demand (US)



task content, along with the substitution effect and faster productivity growth, contributed to the growth of the observed wage bill in the EU-12.

6 Conclusions and further research

Overall, changes in task content were less pronounced in European countries than in the US. Moreover, while in the US the displacement effect predominated over the reinstatement effect, in some European countries the reinstatement effect prevailed over the displacement effect.

Over the periods analysed, as in the US, dominating displacement effect reduced labor demand in Austria, Belgium, Czechia, Germany, Denmark, Spain, Luxembourg, Netherlands, Sweden and Slovakia. Contrary to these results, in Finland, France, Italy, Slovenia and the UK, automation increased labor demand rather than decreased.

Although changes in task content of production were less pronounced in European countries than in the US, there was considerable displacement and reinstatement. Our findings therefore indicate that there was a lot of automation in European countries. While of all the countries analysed, automation was the most significant in Slovakia, there was only limited displacement and reinstatement in France.

The variability in the evolution of the sources of changes in labor demand among European countries and over time identified by the decomposition and the differences identified between the EU-12 and the US call for further research. We therefore plan to identify the factors that cause these differences and to verify whether the change in the task content of production actually captures only (or at least predominantly) displacement effects from automation technologies and reinstatement effects of new tasks (as Acemoglu and Restrepo (2019) did for the US). We also intend to work with longer timer series and collect the missing data for other (European) countries, and not to limit ourselves to data available on the EU KLEMS website. It would be also interesting to explore the sources of changes in labor demand at industry level.

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Tables

Table 1: Worldwide operational stock of industrial robots (IR) (1993-2017)

Year	Number of IR worldwide
1993	555 293
1994	574 496
1995	601 657
1996	640 017
1997	679 364
1998	698 348
1999	719 809
2000	746 333
2001	751 901
2002	765 734
2003	796 363
2004	840 172
2005	913 609
2006	939 244
2007	987 587
2008	1 027 694
2009	1 013 037
2010	1 048 302
2011	1 134 277
2012	1 210 567
2013	1 301 121
2014	1 427 770
2015	1 581 545
2016	1 768 662
2017	2 023 649

Data source: International Federation of Robotics

Table 2: Countries with more than 1 000 industrial robots (IR) per million economically active persons (EAP) in 2017

Country	Number of IR per million EAP
South Korea	9 744
Taiwan	5 081
Singapore	4 814
Germany	4 602
Japan	4 420
Czech Republic	2 847
Slovenia	2 730
Slovakia	2 569
Italy	2 502
Sweden	2 484
Austria	2 226
Denmark	2 122
Belgium	1 821
Hungary	1 634
Finland	1 605
United States	1 596
Switzerland	1 510
Spain	1 408
Netherlands	1 373
France	1 159

Data source: International Federation of Robotics

Table 3: Market and non-market industries

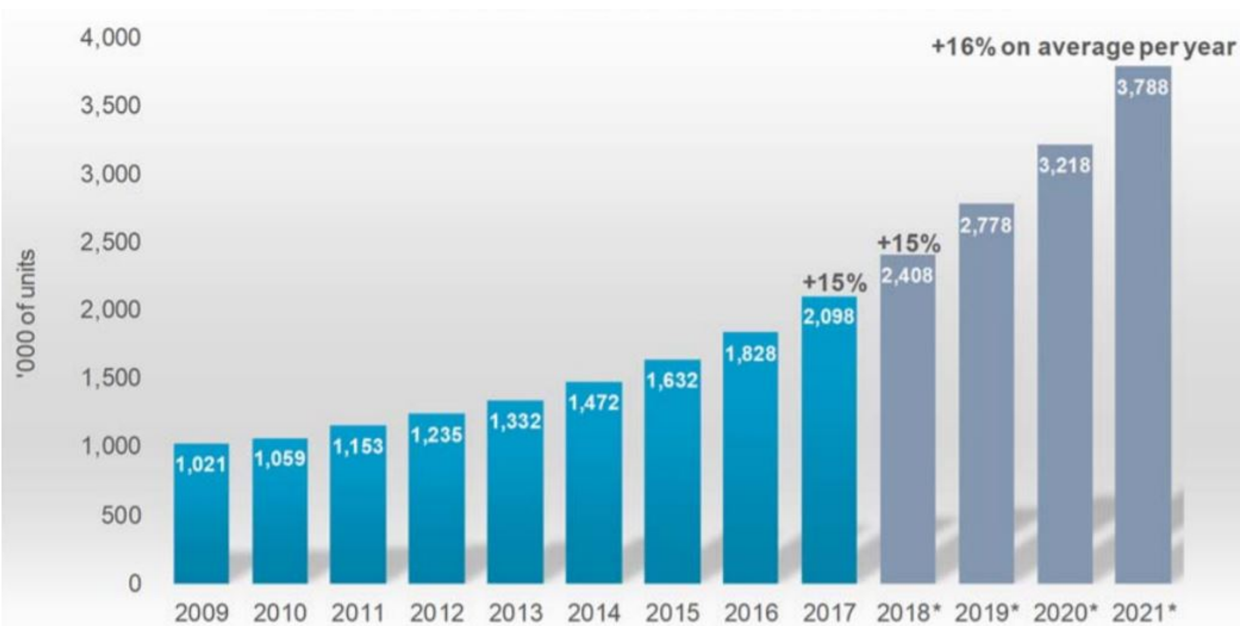
Industry	Code	Economy
Agriculture, forestry and fishing	A	Market
Mining and quarrying	B	Market
Total manufacturing	C	Market
Electricity, gas and water supply	D-E	Market
Construction	F	Market
Wholesale and retail trade; repair of motor vehicles and motorcycles	G	Market
Transportation and storage	H	Market
Accommodation and food service activities	I	Market
Information and communication	J	Market
Financial and insurance activities	K	Market
Real estate activities	L	Non-market
Professional, scientific, technical, administrative and support service activities	M-N	Market
Public administration and defence; compulsory social security	O	Non-market
Education	P	Non-market
Health and social work	Q	Non-market
Arts, entertainment and recreation	R	Market
Other service activities	S	Market
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own us	T	Non-market
Activities of extraterritorial organizations and bodies	U	Non-market

Table 4: Data availability by country

Country	Available data
Austria	1995-2015
Belgium	1999-2015
Czechia	1995-2014
Denmark	1995-2015
Finland	1995-2015
France	1995-2015
Germany	1995-2015
Italy	1995-2014
Luxembourg	2008-2015
Netherlands	2000-2015
Slovakia	2004-2015
Slovenia	2008-2013
Spain	1995-2015
Sweden	1995-2014
United Kingdom	1997-2015
USA	1998-2015

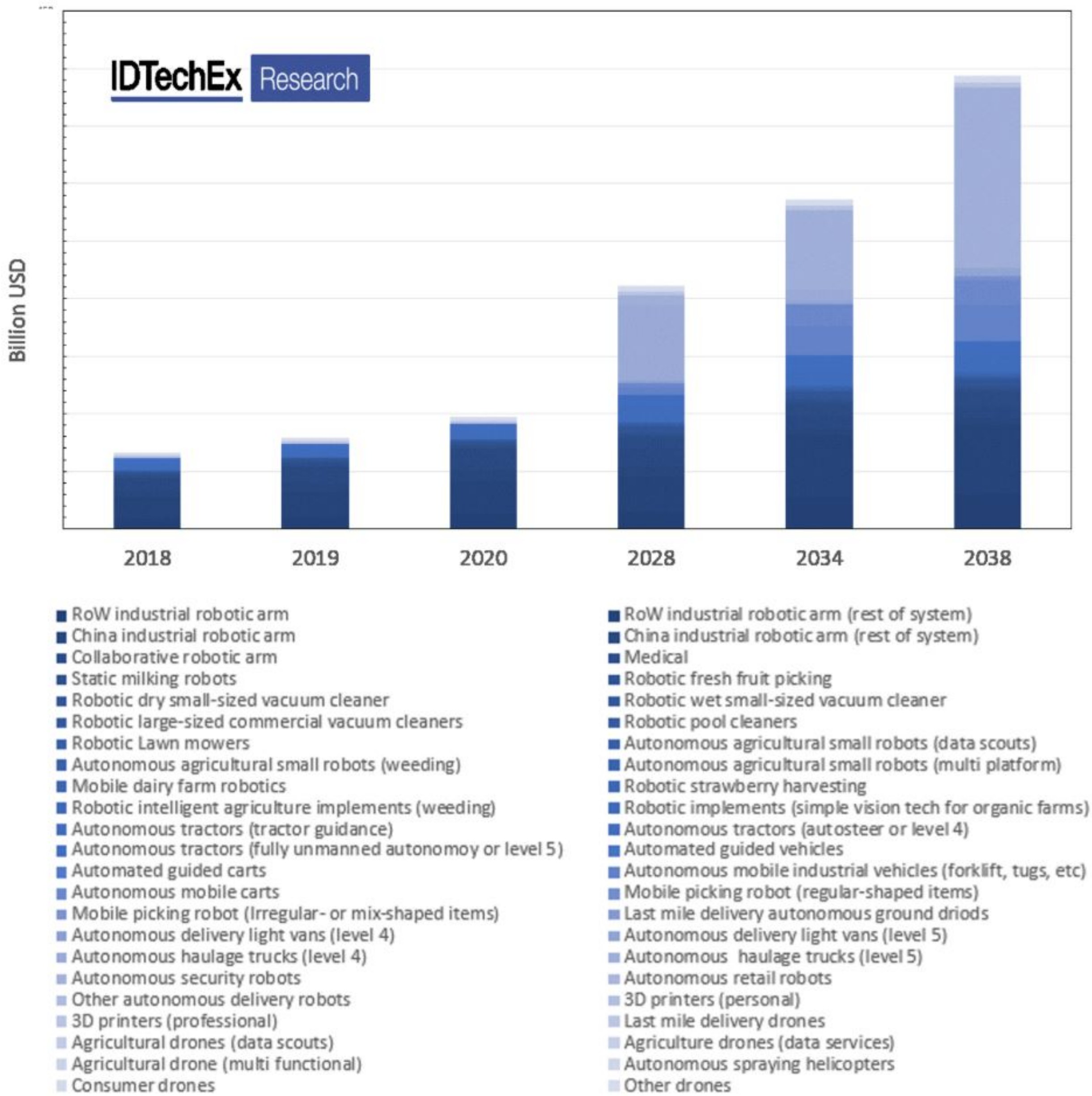
Figures

Figure 4: Estimated worldwide operational stock of industrial robots (2009-2017) and forecast for 2018-2021



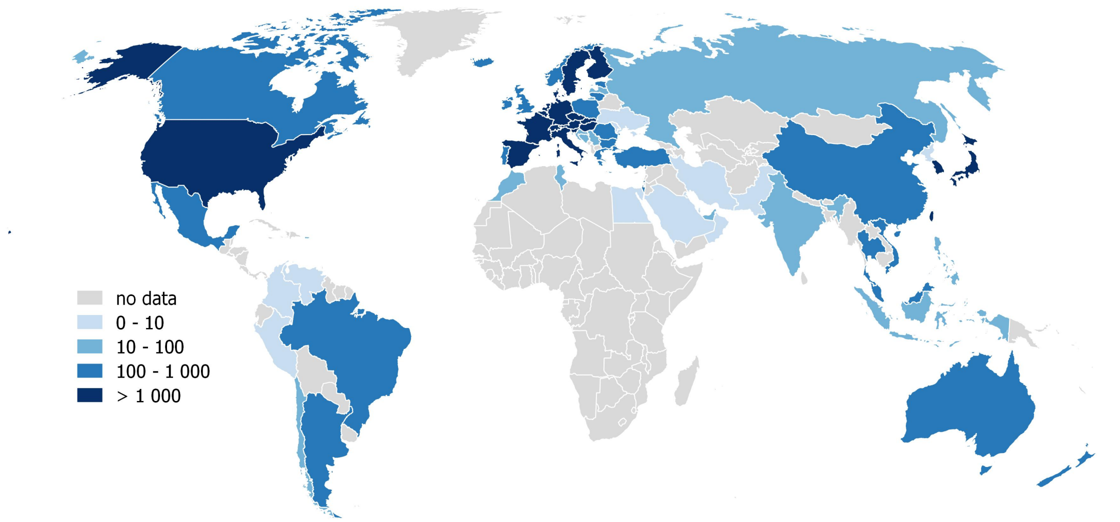
Source: International Federation of Robotics

Figure 5: Market forecasts for 46 robot categories from 2018 to 2038



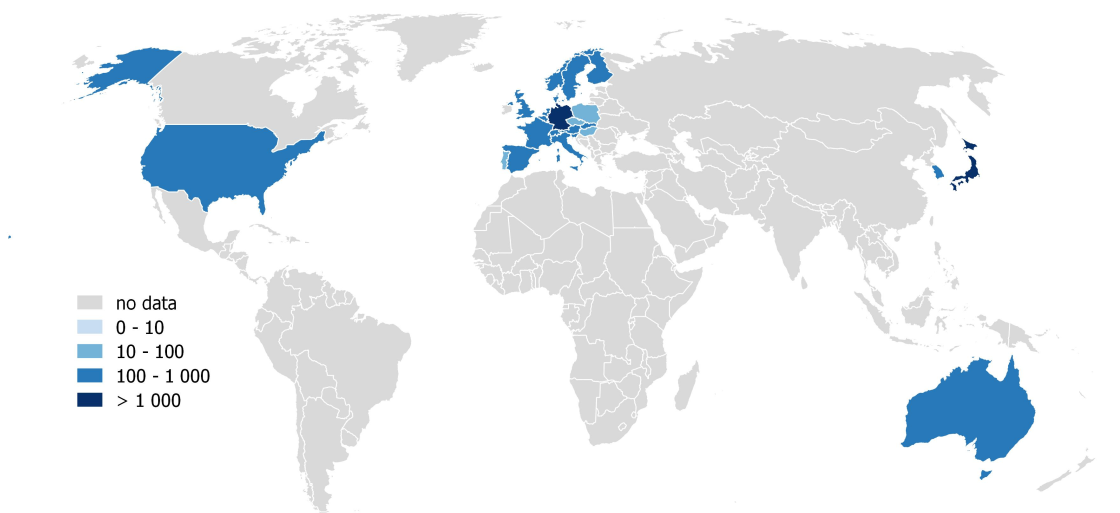
Source: IDTechEx

Figure 6: Number of industrial robots per million economically active persons (2017)



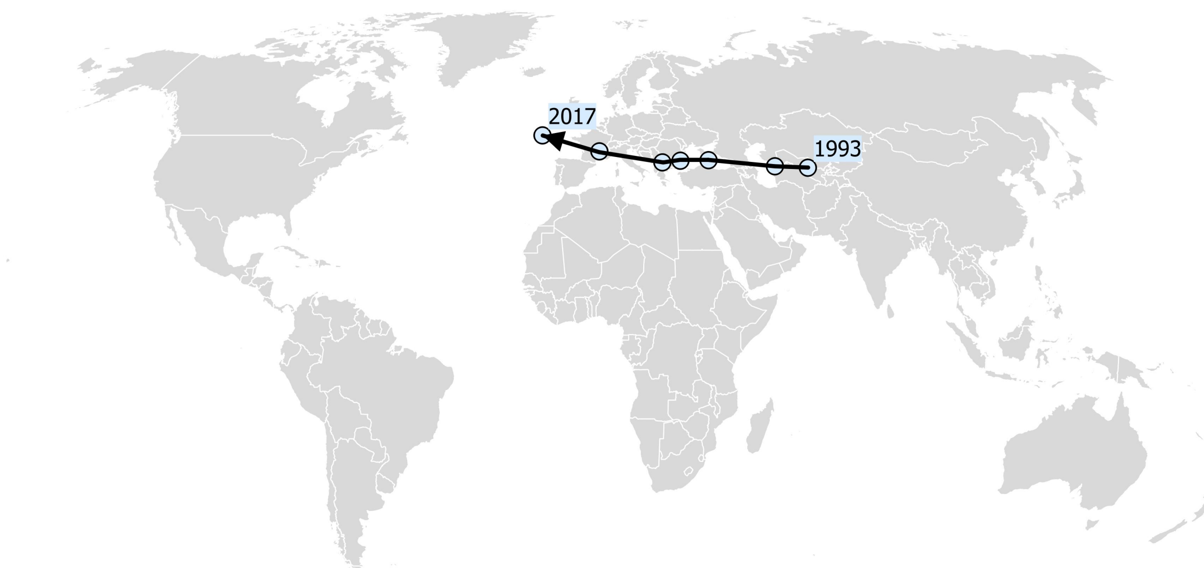
Data source: International Federation of Robotics and World Bank

Figure 7: Number of industrial robots per million economically active persons (1993)



Data source: International Federation of Robotics and World Bank

Figure 8: Geographic centre (centroid) of industrial robots implementation over time



Data source: International Federation of Robotics and World Bank

Figure 9: Sources of changes in labor demand (Austria)

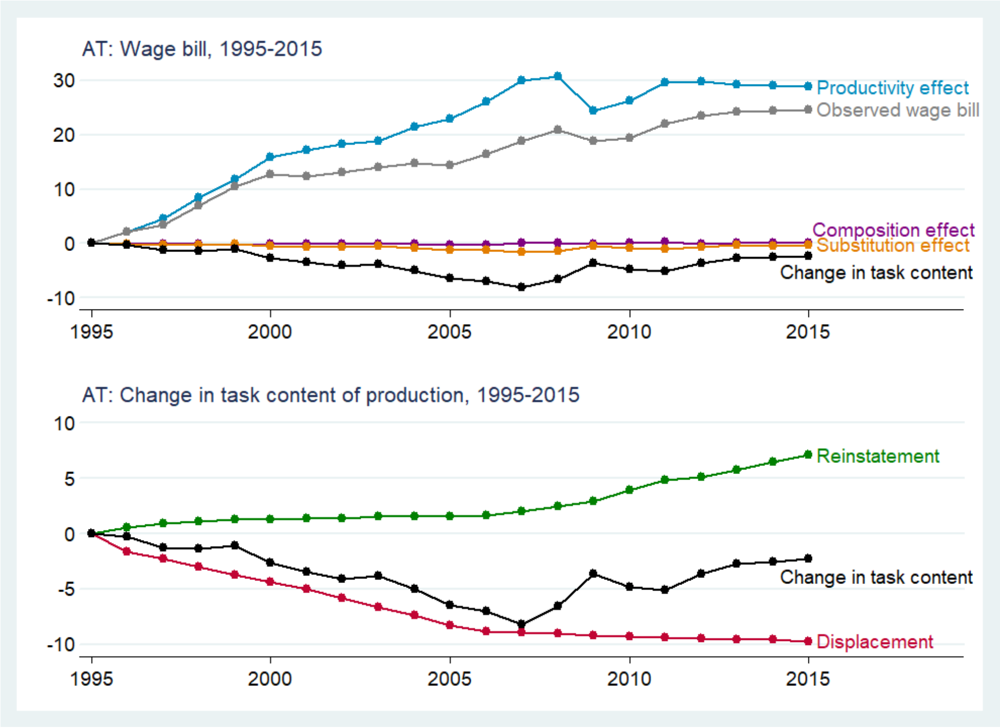


Figure 10: Sources of changes in labor demand (Belgium)

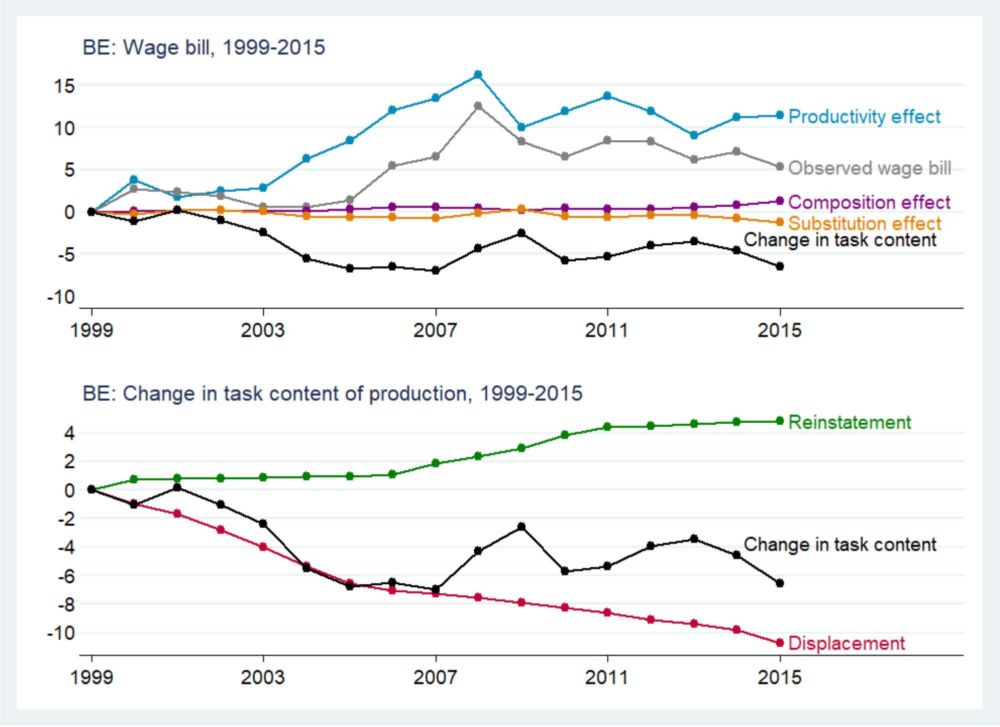


Figure 11: Sources of changes in labor demand (Czechia)

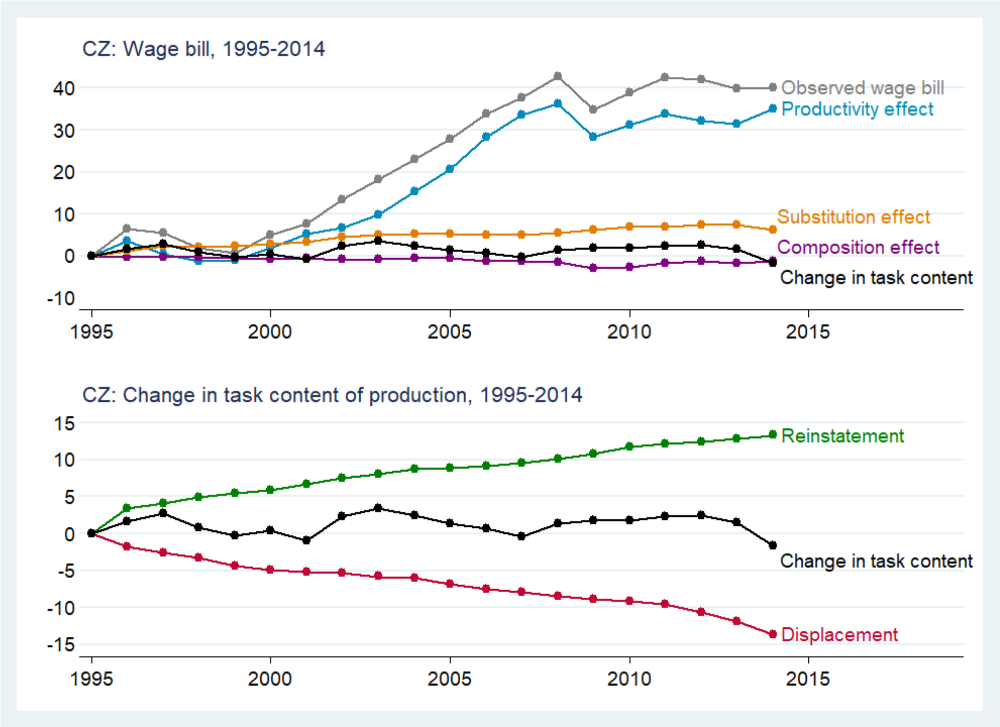


Figure 12: Sources of changes in labor demand (Germany)

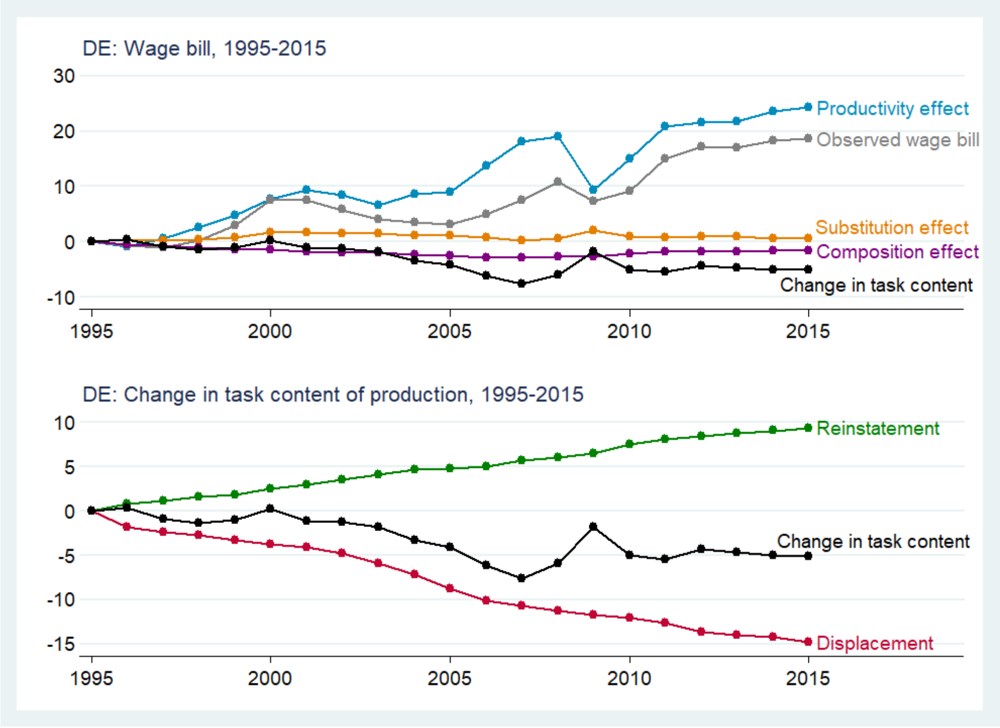


Figure 13: Sources of changes in labor demand (Denmark)

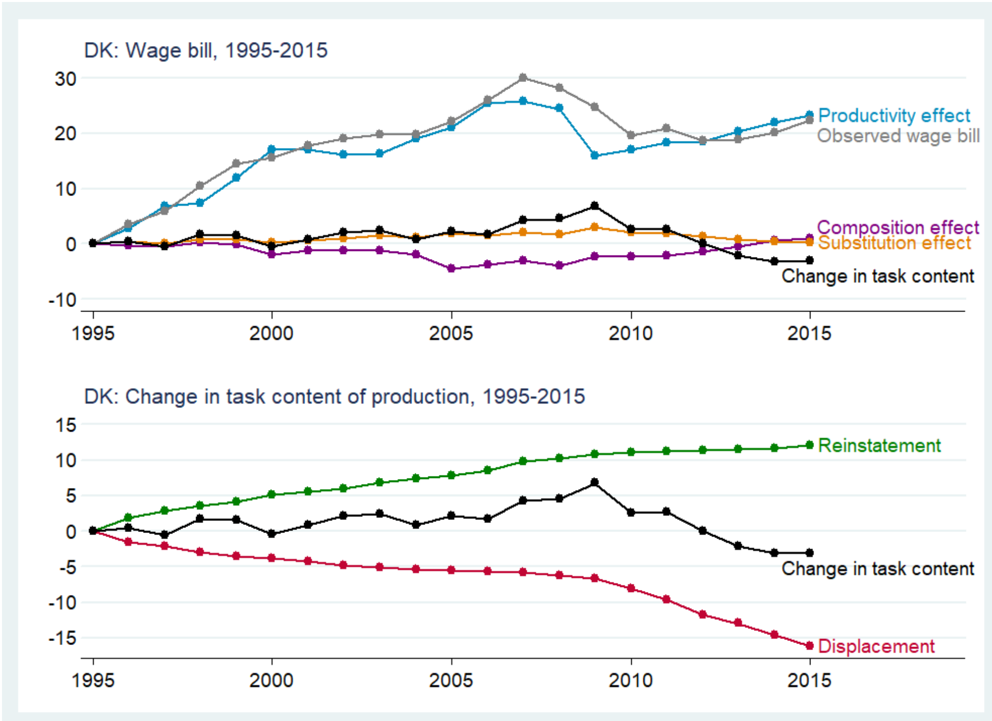


Figure 14: Sources of changes in labor demand (Spain)

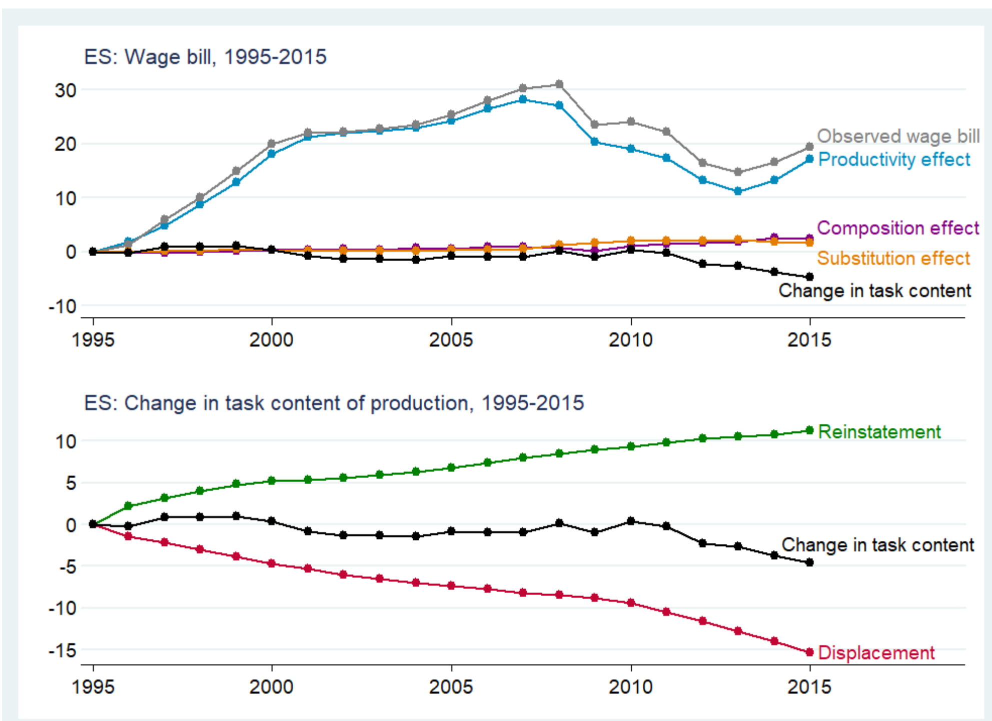


Figure 15: Sources of changes in labor demand (Finland)

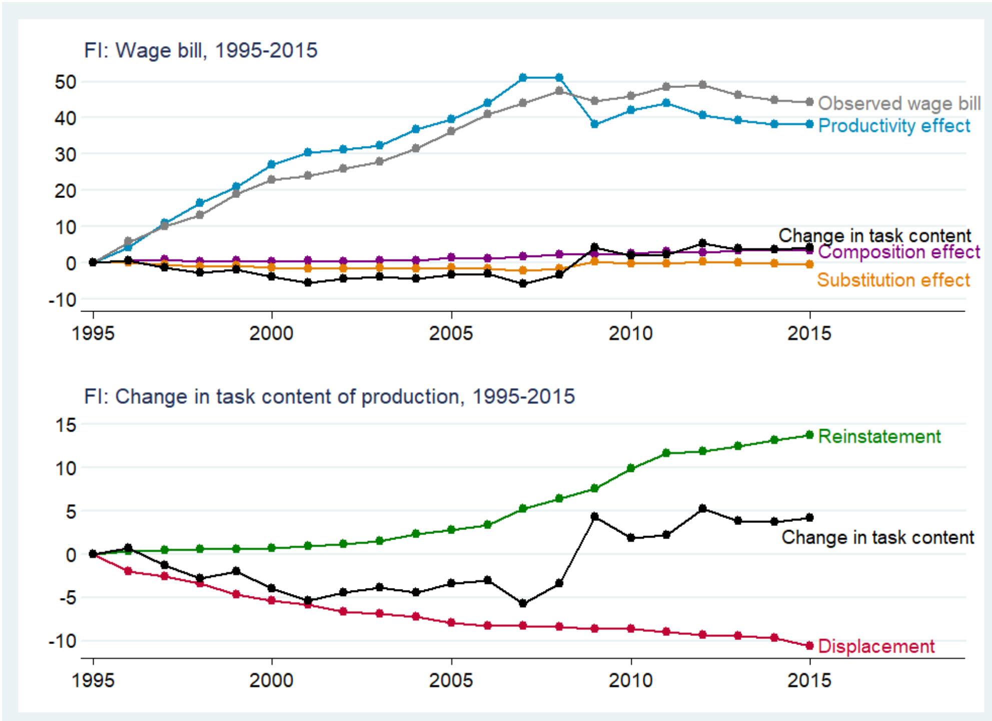


Figure 16: Sources of changes in labor demand (France)

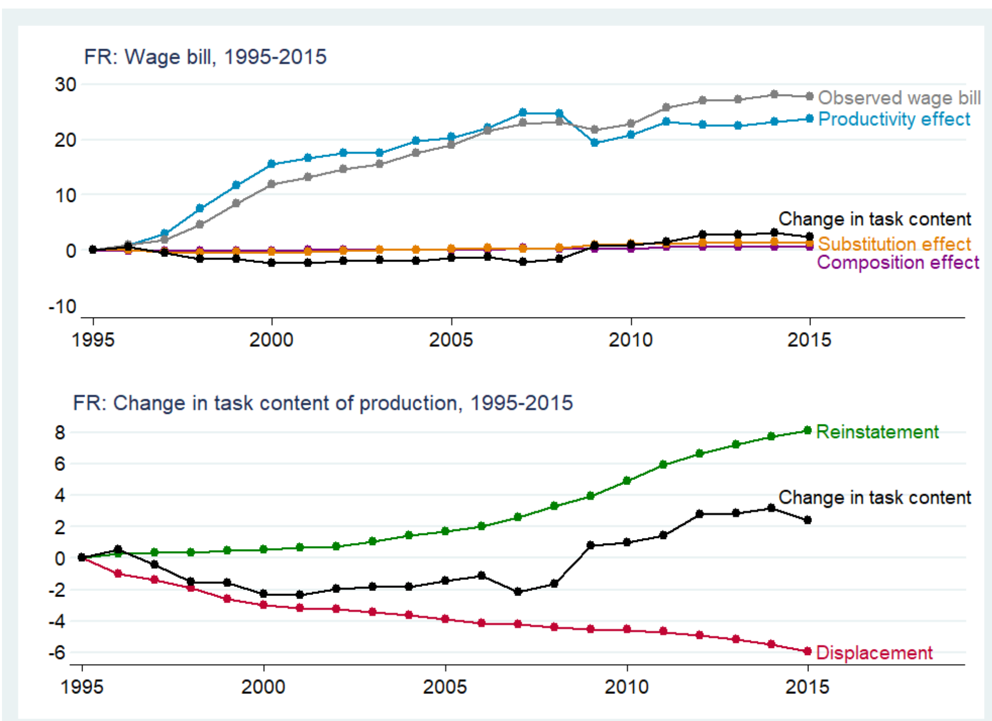


Figure 17: Sources of changes in labor demand (Italy)

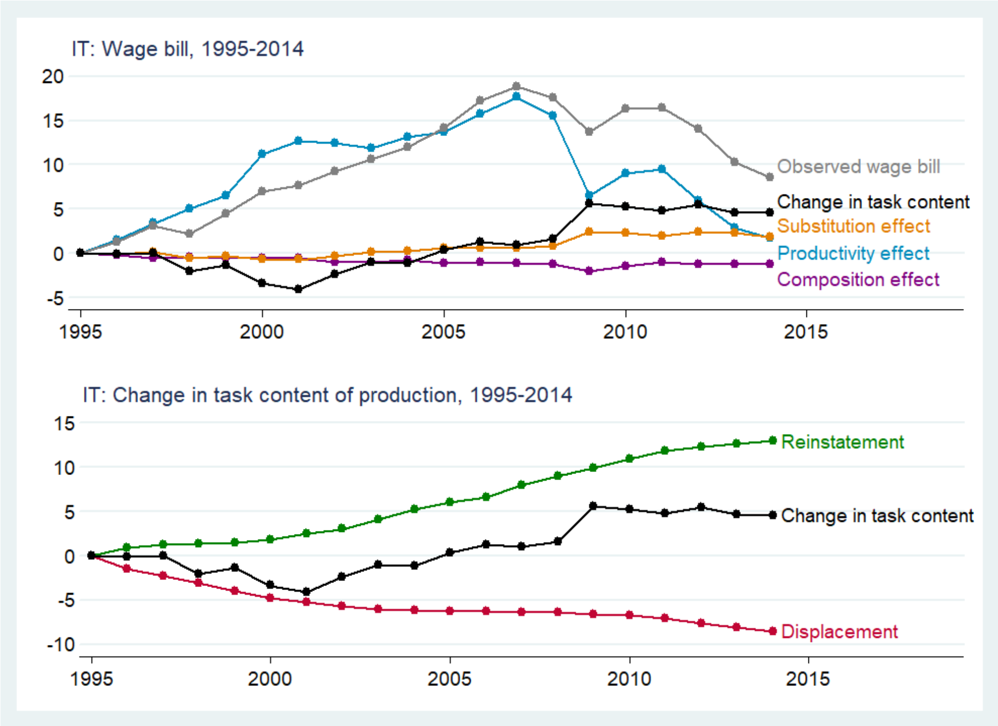


Figure 18: Sources of changes in labor demand (Luxembourg)

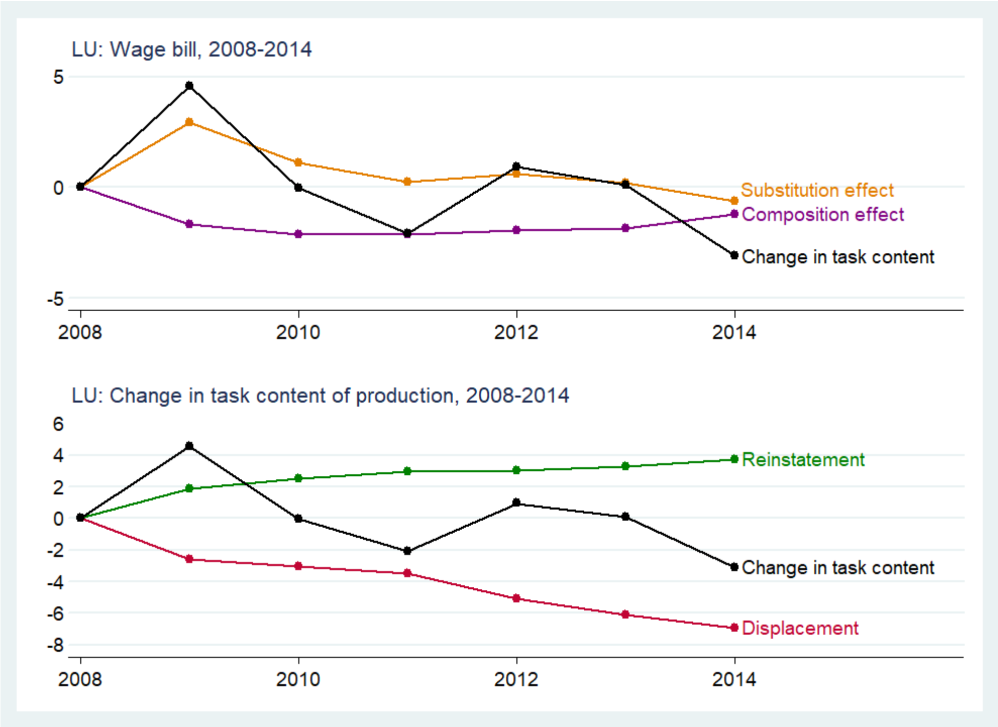


Figure 19: Sources of changes in labor demand (Netherlands)

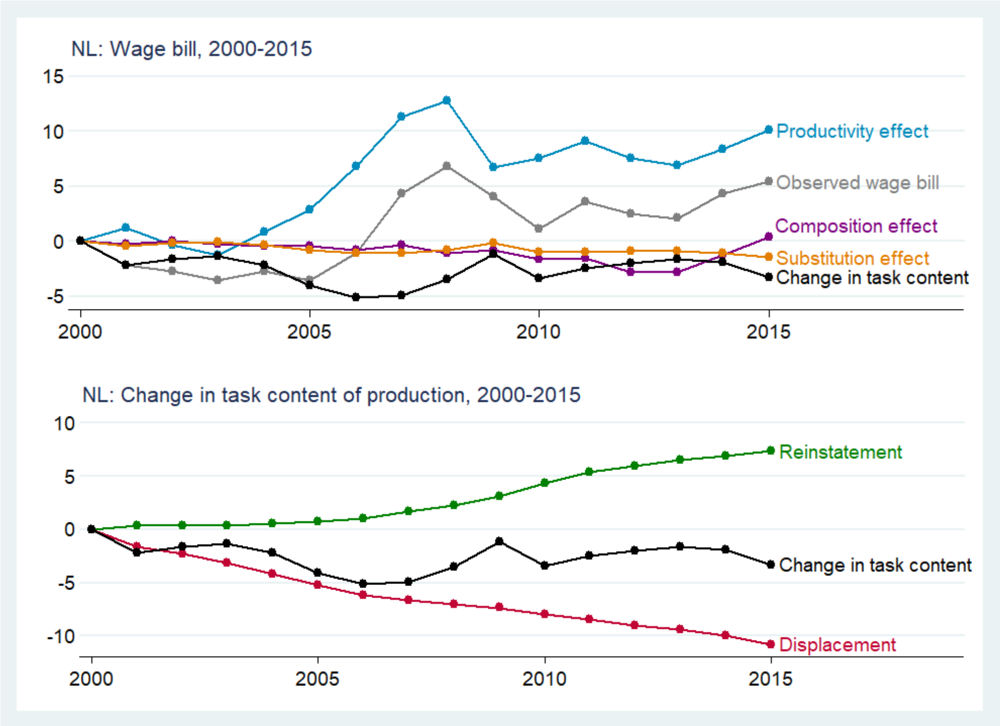


Figure 20: Sources of changes in labor demand (Sweden)

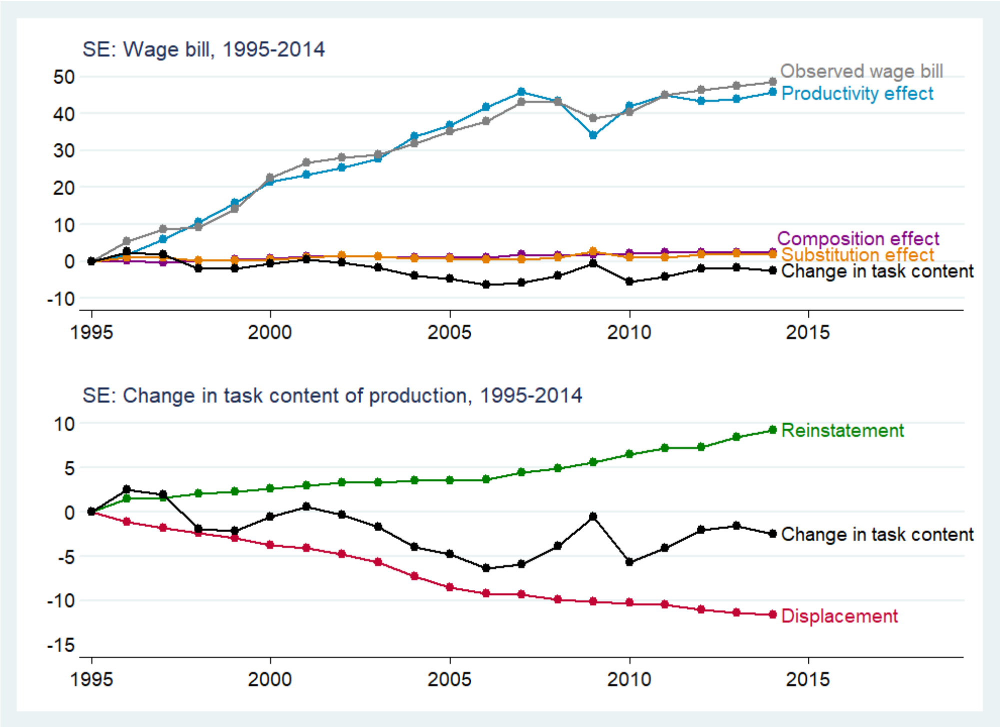


Figure 21: Sources of changes in labor demand (Slovenia)

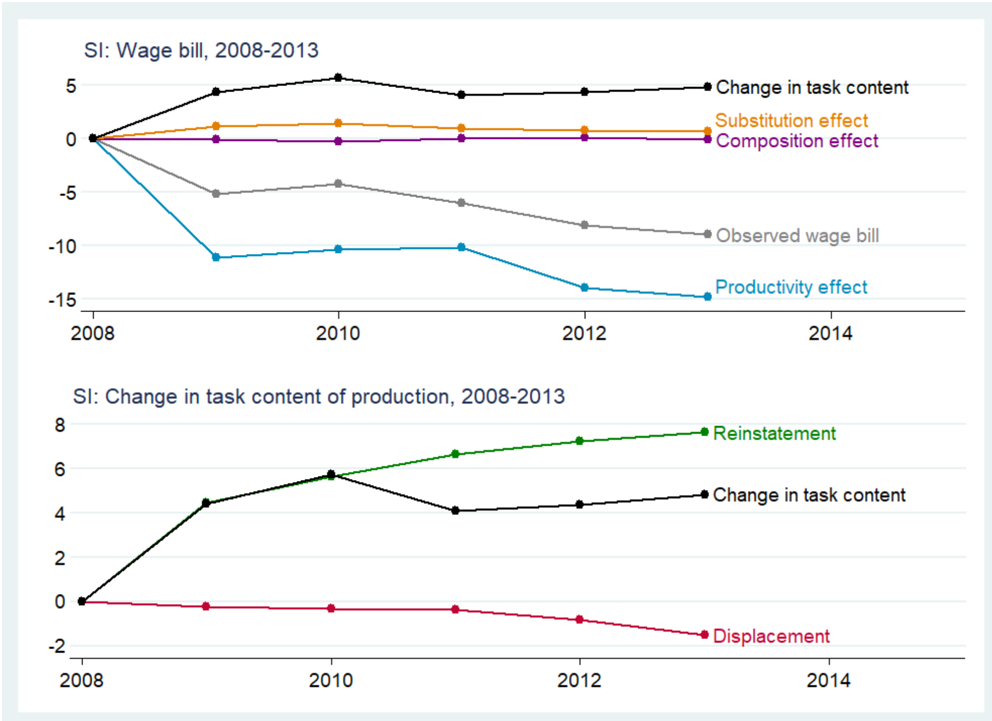


Figure 22: Sources of changes in labor demand (Slovakia)

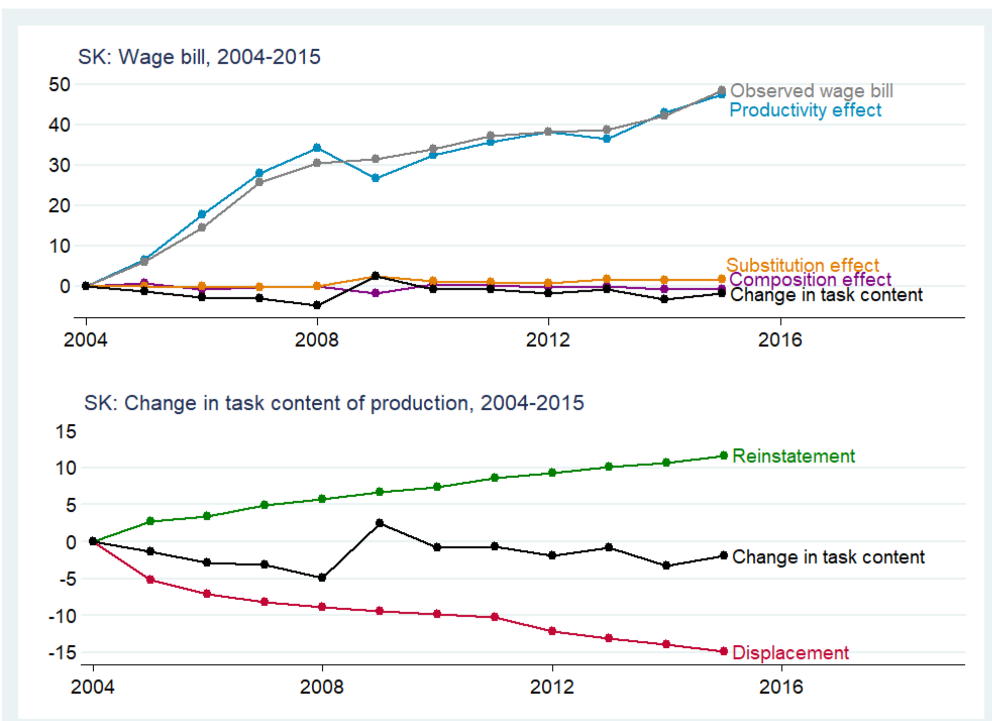


Figure 23: Sources of changes in labor demand (UK)

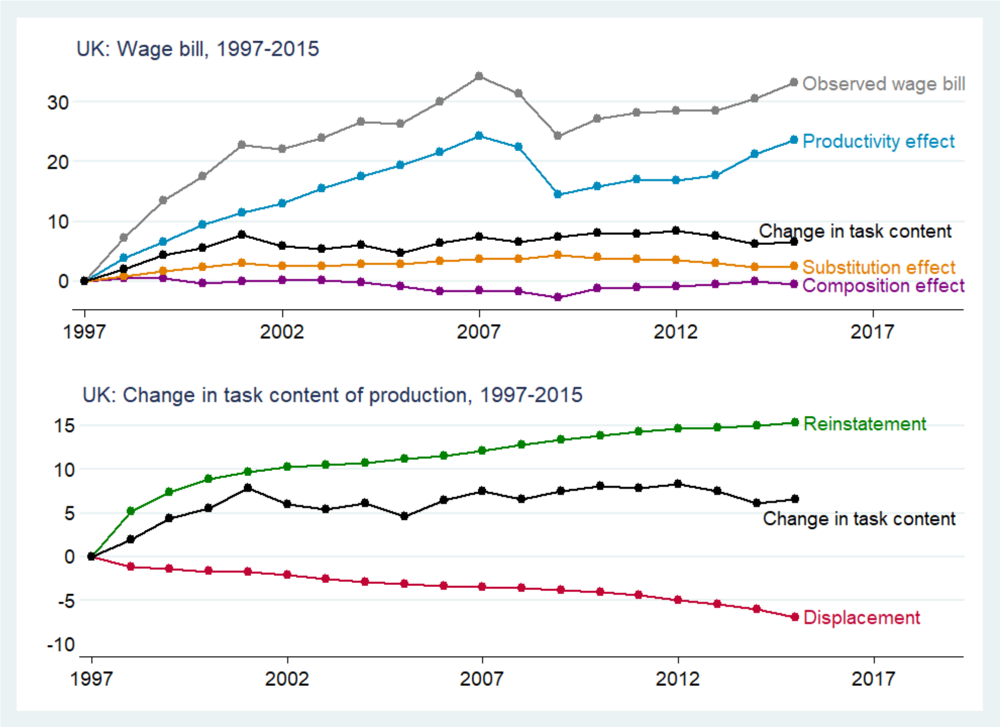


Figure 24: Sources of changes in labor demand (US)