Luiss School of European Political Economy

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Abstract: Drawing on the methodological framework from Acemoglu and Restrepo (2019), this paper investigates the influence of technological innovations on the economy-wide wage bill of four main European countries. The model-based decomposition applied to France, Germany, Italy and Spain shows that: a) the wage-bill deceleration since the 1990s has mainly been productivity driven; b) this deceleration at the same time fell short of productivity dynamics, giving rise to some degree of wage share compression; c) contraction of labor-intensive tasks played a relevant role in such compression; d) this was reflected in an acceleration of technology-induced labor displacement, not sufficiently offset by the reinstatement of new labor-intensive tasks; e) among relevant national specificities, a common feature of the considered countries was labor displacement in service sectors, (particularly the low-end ones). Econometric analysis of factors influencing the displacement effect confirms correlation with specified technology variables (i.e. automation-exposed jobs and investment in software capital).

Keywords: labor share, task changes, automation, inequality, Europe.

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1. Introduction

The discussion on the effect of technological progress on wages and employment is as old as economic science itself. The first arguments about the negative impacts on workers exerted by mechanization date back to Ricardo and Marx. They were then taken up by Keynes (1930) and Leontieff (1952), highlighting the peril of technological unemployment. Right from the beginning of the debate, these risks have been opposed by the counterargument of the positive compensation effects coming from machine adoption, related to both the creation of new job opportunities and to the increase in demand for old and new goods (and hence employment) brought about by growing productivity (early arguments along this line can be found in Steuart and Say, see Piva and Vivarelli, 2017). The recent new wave of automation technologies, which coexists with deteriorating labor-markets, brought new life to this discussion and intensified the controversy between pessimists and optimists. The former think that the very nature of the current technological progress (Artificial Intelligence and robots) is different from the past phases of progress, and that it is capable of leading to widespread displacement of human labor (Frey and Osborne, 2017; Bubbico and Freytag, 2018; Korinek and Stiglitz, 2019). The latter, on the contrary, observe that ongoing automation processes are no different from previous ones and, as those of earlier periods, will in the end raise labor demand, thus positively affecting both wages and employment (Arntz et al., 2016; Bessen, 2020).

At the same time of the revival of such an old debate, the way of thinking about the influences of technological change on productivity and labor demand has gone through a relevant revision. In standard modeling, technology progress is a productivity-strengthening force that either augments one effective input (factor augmenting technical change) or increases the output produced by a given combination of inputs (Hicks-neutral technical change). In this framework the possibility that technology negatively affects labor (equilibrium wage and/or wage share) is quite limited, depending basically on the capital/labor elasticity of substitution that has to assume values that are difficult to observe in reality (Acemoglu and Restrepo 2018a). The new framework that allows for a larger scope of technology is the task-based model built on works developed in the last couple of decades, such as those by Autor et al. (2003), Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018b, 2018c and 2019). According to this modeling, output is produced by combining not inputs, but tasks that are differently allocated to labor and capital. New technologies not only affect factor productivities in specific tasks and across all the tasks (as in standard model), but crucially change the factor task content of production. Particularly automation, beside raising productivity, substitutes capital for human labor in previously labor-intensive tasks, leading to a displacement that unambiguously squeezes the wage share. The effect of automation on labor demand therefore depends on the balancing between the positive and negative influences it exerts on productivity and wage share respectively. At the same time, as history shows, automation periods are also accompanied by more or less intense creation of new, previously inexistent, activities in which labor has a comparative advantage. The introduction of technologies reinstating labor intensive tasks impacts positively both productivity and wage share. The so-called change in task content is the net result between displacement and reinstatement effects brought about by different technical changes. The influence of technology on labor demand depends therefore on the interplay of quite different and opposing forces, whose relative effects can vary in time (positive results of previous technological waves may not replicate if you do not strike the right balance between opposing forces) and space (experience may differ according to how such an interplay takes place in different economies).

The task-based framework is applied by Acemoglu and Restrepo (2019, henceforth, for brevity we refer to this work as A-R) to implement a decomposition model aimed at singling out the different effects of technology change (in the form of both automation and introduction of new tasks) on US labor demand since the postwar period. They find that in the last 30 years, contrary to what happened in the former period, both the wage bill (proxy of labor demand) and the wage share of American workers have been negatively affected by a contraction in the labor content in production tasks. This was due to a deceleration in the introduction of technologies reinstating labor and a concurrent acceleration of technologies displacing it.

In this work we apply the A-R decomposition model to study the role of the task-content change in affecting the wage bill of Germany, France, Italy and Spain over a 47-year period (1970-2017). We expand the original A-R specification by relaxing the assumption of perfect competition in the products market, thus allowing ourselves to explicitly account for the influences of markup changes on the wage bill (through the wage-share channel). Furthermore, we go deeper in exploring the changes in task content by industry to highlight the different sectoral contributions to displacement and reinstatement effects in the considered countries. The decomposition indicates that, even in presence of remarkable country-specific heterogeneities, a deceleration of the wage bill growth takes place in most countries in the last 30 years. A weaker productivity growth is the main driver of such a slowdown, although this does not exhaust the whole story as the wage share compression plays a role too in varying degrees across analyzed economies. The decomposition exercise points out that such reduction also reflects adverse shifts in task content, those related to automation-induced labor displacement not adequately offset by the creation of new labor-intensive tasks. In the European economies, these phenomena are less pronounced than those highlighted by A-R for the US, but they are nonetheless detectable. Particularly, there is a difference in size when comparing the displacement effect experienced by the EU countries with that of the US. Moreover, the considered countries registered some (although insufficient) acceleration of the reinstatement effect in the most recent period, against the deceleration shown in the US according the A-R evidence. A common feature shared by most of the analyzed European countries is the role played by low-tech services in contributing to displacement of labor-intensive tasks, while in the US experience manufacturing is the mostly exposed sector to the acceleration of the displacement effect. These same low-tech services appear to contribute to labor reinstatement in Italy and Spain.

The work is organized as follows. Section 2, reviewing the empirical literature of the effects of automation on labor-market variables in the European countries, illustrates the rather varied backdrop against which the analysis is set. Section 3 goes through the theoretical underpinnings of the A-R decomposition model. Section 4 is dedicated to the description of data sources and discusses adopted calibrations and approximations. Section 5 shows the results of the decomposition model applied to the European countries. Section 6 investigates the driving forces of what was identified in the decomposition exercise as the labor displacement effect. Section 7 concludes the paper.

2. Empirical evidence on European countries.

Besides the A-R decomposition we refer to, several studies are available on the effects of automation on labor-market variables. These studies differ in scope and methods, and, possibly due to a lack of analytical common ground, their findings are sometimes also contradictory. According to the literature, the evidence of a negative correlation between automation and levels of either employment or wages (or both) immediately appears much more heterogeneous in the EU than the US.[1] Empirical results of studies conducted on EU Member States differ according to countries and, even within the same economies, according to methodologies/data/periods (see Table 1 for a summary).

Chiacchio et al. (2018) applied a local market equilibrium model (as in Acemoglu and Restrepo 2017) to verify the impact of robot penetration in six EU countries. They show a significant labor

[1] Regarding the US experience, see Acemoglu and Restrepo (2017), as well as Acemoglu and Restrepo (2019) and Bergholt at al. (2019) for aggregate-level evidence.

displacement effect, but a less relevant impact on wages. In a more recent publication, Klenert et al. (2020) do not find evidence of a job loss, nor of a reduction of employment levels among low skill workers, as a consequence of the introduction of industrial robots in Europe. On the contrary, using the International Federation of Robotics data, from 1995 to 2015 in 28 EU countries, these authors reported a positive trend (even if weak) in the association between robots and overall employment. They estimate an employment increase of 0.2% per each robot introduced for every 1.000 workers. In fact, to similar conclusions pointed the work of Jäger et al. (2016) on the impact of robotics on manufacturing occupation in the main EU countries, highlighting the productivity increases (even in terms of labor) which can be gained thanks to the use of industrial robots. However, they did not obtain any significant evidence (neither of displacement nor of reinstatement) related to the employment levels of surveyed firms within the scope of the 2012 European Manufacturing Survey. Researchers from the EU Commission (Peschner et al., 2018) have also demonstrated how, notwithstanding a displacement mainly affecting routine tasks in manufacturing, robotics industries directly generated new employment and possible job losses have often been complemented by the creation of new opportunities, in innovation and high-tech production sectors and services where workers tasks proved supplementary to those of capital.

However, further studies suggest that, in the occurrence of a totally digitalized working environment, in Germany up to three million jobs could be lost (half of which would represent 1.5 million of current jobs replaced, and the other half would stand for 1.5 million of future jobs never needed) by 2025 (Wolter et al., 2016); and the jobs at risk of automation account for about 59% of total (Brzeski and Burk, 2015). This risk drops to 37.5% in Finland, but considering the high-risk range only (Pajarinen and Rouvinen, 2014). In support of this, an extensive study estimating the share of recently automated employment in 24 EU countries over the 1990-2010 thirty-year period quantifies the total jobs expected to be fully substituted by technology in the next decade in the same countries as ranging from 21% (Ireland) to 45% (Italy) (Lordan, 2018).

Moreover, a deeper assessment of national scenarios produced contrasting results. Other authors (Dauth et al., 2017; Graetz and Michaels, 2017) focused on the German case, which is the main European country in terms of number of robots employed, and they did not detect negative effects on occupation. Conversely, more recently Bonfiglioli et al. (2020) verified how French firms that imported robots between 1994 and 2013 registered both an increase in efficiency and yet a decrease of labor demand. On this same line, Acemoglu et al. (2020) conclude that the adoption of industrial robots in France, between 2010 and 2015, has had a negative impact on both employment and wage share. However, Domini et al. (2017) and then Aghion et al. (2020) instead reported on automation's mainly positive effect in France. Concerning Italy, Dottori (2020) found instead a negative impact of robot adoption only in the case of manufacturing, while the significance of the relation vanishes when considering coexisting and relevant phenomena, as in the use of further technologies (e.g. ICT) or the influence of international trade. Furthermore, microeconomic analyses at workers level have generally shown that those from manufacturing sectors tend not to experience detriments from robotization, with their wages even slightly increasing (based on the length of stay in the initial firm). Finally, it appears that robot diffusion oriented the new workforce towards less mechanized productions. Koch et al. (2019) in the Spanish case obtained a positive effect on firms that adopted industrial robots (with a net job creation rate of 10% and productivity gains by up to 25% over a 4-year period), while a negative one on those who did not, for which a substantial loss of jobs occurred; the overall labor share seems to be penalized. With a similar study on Dutch data, Bessen et al. (2019) refuse the hypothesis of a complete labor displacement by automation. Distinguishing firms based on their choices to invest or not in automation, these authors obtain opposite results compared to Koch et al. (2019): employees of automating firms turn out to have either experienced a yearly wage cut of 11% or left their job (2 percentage points more likely than their counterparts in non-automating firms), with an overall negative effect on labor (cost) share.

The heterogeneous findings of different analyses also show the relation of the objects of these studies with the specificities of the economic structures of considered countries. The total effect of automation on labor will depend also on the workforce exposition rate to these technologies and, bearing in mind for example that 99% of installed robots in the EU pertain to manufacturing (IFR database), the result will strongly be influenced by the weight of this sector within the national production system (Chiacchio et al., 2018). In addition, a variety of results relies on technical differences of used datasets: it seems that analyses on microeconomic statistics tend to produce non-significant or positive estimates, while aggregate data at sectoral or national levels more often provide a negative outcome (Klenert et al., 2020).

A relevant aspect of the automation effects on jobs is related to routine tasks, which are considered more at risk of being automated. For this same reason, they can be used (as we do in Section 6) as a proxy to quantify the penetration of automation technologies when variables directly measuring technological change are missing. That is why, together with studies on robots and other automation technologies (e.g. IT, AI, etc.), it is relevant here to refer also to the work of the scholars who have delved further into the polarization of occupations related to robotization of production tasks (Darvas and Wolff, 2016, on six EU countries), or the pervasive impact of routine tasks on labor market (Goos et al., 2016, in sixteen countries of western Europe), finding a significant increase in Europe as well. In the Norwegian case, Akerman et al. (2015) analyzed the IT investment effects, suggesting that adopting these technologies is complementary in case of non-routine tasks assigned to specialized workers, while it tends to substitute labor in the opposite case of routine tasks performed by low-average skilled workers. In a similar manner, Gaggl and Wright (2017) have reported that the ICT technologies adoption in the UK supported the non-routine and highly-cognitive expertise, but often in association to increased wage inequalities within the firms. With a crosscutting analysis on 27 EU countries, Gregory et al. (2019) show that the substitution of routine tasks by automating technologies (*routine-replacing technological change*, RRTC), occurring between 1999 and 2010, produced substantial labor displacement, but at the same time a net employment increase was made possible by a concurrent and significant reinstatement effect. The same authors conclude, however, that this result is conditional on the distribution of technological progress gains.

On the same page, the elaboration made by Eurofound (2016, 2017) on monitoring job tasks changes in the EU explains how identifying the effect of technology, as those of international trade or other factors affecting production inputs, is not enough to adequately estimate the related change in employment levels. Adopting a task-based approach makes evident the role of each single task, which have no real value on their own but do count in their interrelation with each other in a specific production combination, and clarifies that their recombination is what determines the final effect on employment structure.

Given this quite varied backdrop, our contribution focuses on the influence of automation technologies on the most comprehensive measure of the labor-market situation, namely the economy-wide wage-bill changes that are affected by the intensity with which both positive and negative technology-induced effects take place. As will become apparent in the empirical testing, we do not limit our analysis to the strict automation definition of technological change as available in automation-related statistics (such as automation-exposed jobs or multi-use industrial robots) because they do not seem completely adequate to allow for the displacement phenomena occurring in non-industrial sectors that are relevant in the considered economies. We perform our analysis by applying a methodology originally tailored for the specific case of the US labor market and, as such, useful for providing a directly comparable finding about the main EU countries.

Table 1. Overview of studies on the innovation impact on labor in European countries

Studied technology	Country	Authors	Effects on labor	Notes / Analyzed period
Automation				
	Finland	Pajarinen and Rouvinen (20	- (workers)	% high risk of automation / 2012
	France	Aghion et al. (2020)	+ (workers)	1994-2015
	France	Domini et al. (2017)	+ (workers)	2002-2015
	Germany	Brezski e Burk (2015)	- (workers)	% risk of automation / 1994-2014
	Netherlands	Bessen et al. (2019)	- (workers) - (wages)	2000-2016
	20 UE countries 238 regions	Gregory et al. (2019)	 + (workers)	1999-2010 reinstatement > displacement
	EU	Peschner et al. (2018)	+ (workers) - (routine tasks)	robotics / 1993-2016 manufacturing
Industrial robots				
	France	Bonfiglioli et al. (2020)	- (workers)	1994-2013
	France	Acemoglu et al. (2020)	- (workers) - (labor share)	2010-2015
	Germany	Dauth et al. (2017)	0 (workers)	1994-2014
	Italy	Dottori (2020)	+ (wages) 0 (workers) - (workers)	1993-2016 economy-wide manufacturing
	Spain	Koch et al. (2019)	+ (workers) - (labor share) + (wages)	1990-2016
	6 EU countries	Chiacchio et al. (2018)	- (workers) 0 (wages)	1995-2007
	7 EU countries	Jäger et al. (2016)	0 (workers)	manufacturing / 2009-2012
	24 EU countries	Lordan (2018)	- (workers)	% automatable jobs / 1990-2010
	EU28	Klenert et al. (2020)	+ (workers)	1995-2015
ICT/ artificial intelligence				
	Germany	Wolter et al. (2016)	- (workers)	forecasts 2017-2035
	Norway	Akerman et al. (2015)	- (routine tasks)	low skill > high skill /2001-2007
	United Kingdom	Gaggl and Wright (2017)	- (wages)	2001-2004

3. Model-based decomposition of the wage bill: the A-R framework

In this section we go through the rationale and theoretical underpinnings of the A-R model that is then applied to the case of the European countries.

Wage-bill identity

At the base of the decomposition exercise is the economy-wide wage-bill identity that, at time *t*, is given by

$$W_t L_t \equiv P_t Y_t \, x \, s_t^l \equiv P_t Y_t \, x \sum_i \chi_{it} \, s_{it}^l \ldots\ldots\ldots\ldots\ldots\ldots \textit{(1)}$$

Where W_t is the wage rate, L_t is the number of persons employed, Y_t is the real value added, P_t is the value-added price index, s_t^l is the wage share, χ_{it} is the weight of the *ith*-sector in the value added of the economy $\left(\chi_{it} = \frac{P_{it}Y_{it}}{P_t Y_t}\right)$ and s_{it}^l is *ith*-sector wage share $\left(s_{it}^l = \frac{W_{it}L_{it}}{P_{it}Y_{it}}\right)$. Expression *(1)* allows for an exact decomposition of the wage-bill log-changes in the log changes of the right-hand side variables, namely the economy-wide value added and the wage share. The latter can in turn be exactly decomposed in the log changes of sector composition and sector wage shares. The insertion of this simple identity in the A-R formal model considerably enlarges the scope of the interpretation of the economic forces affecting it.

Task-dependent wage share

The task-based framework of Acemoglu-Restrepo (2019) exploits the wage-bill identity to highlight the influence of task changes on labor demand, where the latter is identified with the changes of the wage bill that summarize combinations of (un-investigated) variations in the price and quantity of the labor input. The channel through which changes in tasks affect the wage bill is a task-dependent formulation of the sector wage shares, s_{it}^l. To arrive at a task-dependent expression of the wage share, the A-R model assumes that output (real value added) is obtained by the combination of a range of tasks which, in turn, are produced using capital and labor. Automation takes place whenever capital substitutes for labor in some (previously) labor-intensive tasks. In this framework, (equilibrium) output can be represented as a constant elasticity substitution (CES) function of capital and labor.

$$Y_{it} = \Pi_{i\,t}\left(\Gamma_{it}^{\frac{1}{\sigma}}\left(A_{it}^L L_{it}\right)^{\frac{\sigma-1}{\sigma}} + \left(1-\Gamma_{it}\right)^{\frac{1}{\sigma}}\left(A_{it}^k K_{it}\right)\right)^{\frac{\sigma}{\sigma-1}}$$

Where A_{it}^L and A_{it}^k are labor- and capital-augmenting technologies increasing the productivity of labor (*L*) and capital (*K*) in all the tasks performed with these inputs; $\sigma \geq 0$ is the elasticity of substitution between tasks, and it coincides with the derived elasticity of substitution between capital and labor; $\Pi_{i\,t}$ is the total factor productivity. As such, the former expression is quite similar to a standard CES production function but for the fact that the share parameters, $\Gamma_{it}^{\frac{1}{\sigma}}$ and $(1-\Gamma_{it})^{\frac{1}{\sigma}}$, are not constant, as they depend on task contents that modify whenever automation processes and introduction of new tasks occur. Particularly, the term Γ is the labour task content of production, measuring the share of labour-performed tasks relative to all tasks (and conversely, the term (*1* - Γ) is the capital task content of production measuring the share of tasks produced by capital). The expression for labor task content is hence given by

$$\Gamma_{it} = \frac{\int_I^N \gamma_{it}^L(z)^{\sigma-1}dz}{\int_{N-1}^I \gamma_{it}^K(z)^{\sigma-1}dz + \int_I^N \gamma_{it}^L(z)^{\sigma-1}dz}$$

Where *z* is the range of all tasks, normalized to vary between *N-1* and *N*. Task *I*, with *N-1 < I < N*, denotes the threshold task dividing labor-intensive from capital-intensive tasks: for *z > I*, tasks are not automated and are produced only with labor; for *z ≤ I*, tasks are automated and produced only with capital. It follows from the former expression that the labor task content, *Γ*, shrinks as *I* increases (more tasks previously performed with labor are automated, with a consequent labor displacement), and enlarges as *N* rises (new labor-intensive tasks are introduced, with a consequent labor reinstatement). Parameters γ_{it}^{L} and γ_{it}^{k} identify the labor and capital productivity in producing the specific task *z*. They are task-specific factor productivities differing from the factor-augmenting technologies, A_{it}^{L} and A_{it}^{k}, that affect factor productivities across all tasks in which labor and capital are involved.

Moving away from the A-R framework, we take account of deviations from perfect competition in product markets. At the same time, we retain the assumption that the labor market is perfectly competitive or that, if there is bargaining between firms and workers over possible rents, firms are, however, able to stay on their labor demand schedules. Given these assumptions, and denoting by *R* the rental rate of capital, the CES structure of the production function leads to the (task-dependent) wage share in the *i-th* sector

$$s_{i\,t}^{l} = \frac{1}{m_{it}} \frac{1}{1+\frac{1-\Gamma_{it}}{\Gamma_{it}}\left(\frac{A_{it}^{L}}{W_{it}}\ \frac{R_{it}}{A_{it}^{K}}\right)^{1-\sigma}} \qquad (2)$$

Where $m_{it} \geq 1$ is the possible markup (when $m_{it} > 1$) charged by firms of the *i-th* sector.

As in canonical models, the wage share depends on the ratio of effective factor prices $\frac{R/A^{k}}{W/A^{l}}$: as W/A^{l}rises relative to R/A^{k}, prices of tasks produced by labor rise relative to those produced by capital. This causes a substitution between tasks (capital-intensive tasks taking over labor-intensive ones) and an impact on the wage share that depends on whether σ < 1 (wage share rises) or > 1 (wage share reduces). Consideration of imperfect competition in the output market introduces the influence of firms' pricing practices on the wage share: as markups over marginal costs (m_{it}) rise, the wage share diminishes. What is novel in this framework, compared to the standard model, is the fact that the wage share depends also on the change of the task content of production: as more tasks are allocated to capital ($\Gamma\downarrow$), task content shifts away from labor and the wage share declines; conversely the introduction of new (labor-intensive) tasks ($\Gamma\uparrow$) increases the wage share. This is quite a different effect from the substitution between tasks, and it takes place independently of changes in factor prices and the elasticity of substitution.

In the A-R framework, automation reduces the wage share unambiguously. This influence can be offset by the opposite force represented by the adoption of technologies reinstating new labor-intensive tasks, provided that such a process occurs at a sufficient pace to compensate the automation-induced labor displacement. Besides changing task content, automation can also affect the wage share via a substitution effect if it induces factor-biased technological changes that alter the relative remuneration of effective inputs. In addition to the wage-share channel, automation directly impacts the wage bill through the general productivity improvement (an effect that is incorporated in the value-added term of the wage bill identity) and the shift in the economy's sector composition (between sectors characterized by different wage shares). All these effects are exhaustively embedded in the model-based decomposition of the wage-bill identity *(1)*.

Decomposing the change of the real (per-capita) wage-bill

For the sake of time and space comparability, both the economy-wide value added and the wage bill in *(1)* are normalized by the population, so that changes of these variables are considered in per-capita terms. Substituting *(2)* in *(1)*, total differentiation of the wage-bill identity leads to

$$L_t dW_t + W_t dL_t = d(P_tY_t)\sum_i \chi_{i\,t} s^l_{i\,t} + (P_tY_t)\sum_i s^l_{i\,t} d\chi_{i\,t} + (P_tY_t)\sum_i \chi_{i\,t} ds^l_{i\,t}$$

Using the definitions $\chi_{it} = \frac{P_{it}Y_{it}}{P_tY_t}$ and $s^l_{i\,t} = \frac{W_{it}L_{it}}{P_{it}Y_{it}}$ and adopting the further definition $l_{it} = \frac{W_{it}L_{it}}{W_tL_t}$ indicating the wage-bill share generated in the *i-th* sector, the former expression becomes

$$\frac{dW_t}{W_t} - \frac{dL_t}{L_t} = \frac{d(P_tY_t)}{P_tY_t}\sum_i l_{it} + \sum_i \frac{s^L_{it}}{s^L_t}\, d\chi_{it} + \sum_i l_{it}\frac{ds^L_{it}}{s^L_{it}}$$

where s^L_t is the economy-wide wage share. In terms of natural log-differentiation, the expression for the real wage-bill change is written as

$$dlnW_t + dlnY_t - dlnP_t = dlnY_t + \textstyle\sum_i \frac{s^L_{it}}{s^L_t} d\chi_{i\,t} + \sum_i l_{it}\, dln\, s^L_{it} \qquad (3)$$

where $dln\, s^L_{it}$ can be obtained by totally differentiating *(2):*

$$dln\, s^L_{it} = dln\left(\frac{1}{m_{it}}\right) + \frac{1-m_{it}s^L_{it}}{(1-\Gamma_{it})} dln\Gamma_{it} + (1-\sigma)\left(1-m_{it}s^L_{it}\right)\left[dln\left(\frac{W_{it}}{A^L_{it}}\right) - dln\left(\frac{R_{it}}{A^K_{it}}\right)\right]$$

Substituting this in *(3),* we finally get the complete expression of the decomposition of the (per-capita) real wage-bill change:

$$\begin{aligned}
dln\frac{W_tL_t}{P_t} \quad = \quad & dlnY_t && (productivity\ effect)\\
& + \sum_i \frac{s^L_{it}}{s^L_t}\, d\chi_{i\,t} && (composition\ effect)\\
& + \sum_i l_{it}\ dln\left(\frac{1}{m_{it}}\right) && (markup\ effect)\\
& + \sum_i l_{it}\frac{1-m_{it}s^L_{it}}{(1-\ \Gamma_{it})} dln\Gamma_{it} && (change\ in\ task\ content)\\
& + \sum_i l_{it}\,(1-\sigma)\left(1-m_{it}s^L_{it}\right)\left[dln\left(\frac{W_{it}}{A^L_{it}}\right) - dln\left(\frac{R_{it}}{A^K_{it}}\right)\right] && (substitution\ effect)
\end{aligned}$$

Note that in this expression the change in task content identifies labor displacement whenever Γ moves following an increase of the threshold-task *I*, while it identifies labor reinstatement whenever Γ moves following an increase of the upper-limit task *N*. Moreover, in the expression, the composition, markup, change-in-task-content and substitution effects perfectly add up to the log change of the economy-wide wage share that enter the wage-bill identity.

Decomposition of the wage bill: from theory to practice

The continuous-time model shows how infinitesimal changes of the wage bill can be decomposed into changes of the set of completely identified components shown in the right-hand side of the former expression. This is an exact (exhaustive) decomposition, in which each effect is identified, given the model assumptions. Yet, going from theory to practice approximations are needed for two reasons. First, you have to deal with discrete-time variables. Secondly, the variable Γ is empirically unobservable, precluding any independent estimation of the term representing the change in task content. Both these elements cause the implementation of the decomposition to depart from the theoretical model, which has to be properly proxied when performing the empirical exercise.

Consider the identity of the empirically-measured (per capita) real wage bill at time t_0 and t:

$$W_{t_0}L_{t_0}/P_{t_0} \equiv Y_{t_0}\sum_i \chi_{i\,t_0} s^l_{i\,t_0}$$

$$W_t L_t / P_t \equiv Y_t \sum_i \chi_{it} s_{i\,t}^l$$

Taking the natural-log difference yields:

$$ln(W_t L_t/P_t) - ln\left(W_{t_0} L_{t_0}/P_{t_0}\right) \equiv ln\ Y_t - lnY_{t_0} + \ln\left(\sum_i \chi_{it} s_{i\,t}^l\right) - ln\left(\sum_i \chi_{i\,t_0} s_{i\,t_0}^l\right) + ln\left(\sum_i \chi_{i\,t_0} s_{i\,t}^l\right) - ln\left(\sum_i \chi_{i\,t_0} s_{i\,t}^l\right)$$

From which an exact decomposition of the change of the (empirically measured) real wage bill follows:

$$\begin{aligned} ln(W_t L_t/P_t) - ln\left(W_{t_0} L_{t_0}/P_{t_0}\right) \equiv\ & ln\ Y_t - lnY_{t_0} && (empirical\ productivity\ effect) \\ & + ln\left(\sum_i \chi_{it} s_{i\,t}^l\right) - ln\left(\sum_i \chi_{i\,t_0} s_{it}^l\right) && (empirical\ composition\ effect) + \\ & + ln\left(\sum_i \chi_{i\,t_0} s_{i\,t}^l\right) - ln\left(\sum_i \chi_{i\,t_0} s_{i\,t_0}^l\right) && (empirical\ wage\ share\ change) \end{aligned}$$

A-R show that this discrete-time decomposition of the real wage bill leads to 1st-order Taylor approximations of each element of the model-based decomposition (see Appendix 1 for a demonstration applied to the markup-augmented version of the A-R model). Moreover, given the unobservability of Γ, the term representing the change-in task-content effect can be obtained by exploiting the fact that, under the model assumptions, the sector wage-share change exactly decomposes into markup, substitution and change-in-task-content effects. Therefore, the latter can be derived as a residual, from the identified effects as follows:

$$change\ in\ task\ content\ in\ the\ ith\ sector = lns_{it}^L - lns_{it_0}^L - \left(ln\left(\frac{1}{m_{it}}\right) - \ln\left(\frac{1}{m_{it_0}}\right)\right) - \left(1 - m_{it_0} s_{it_0}^L\right)(1-\sigma)\left(ln\left(\frac{W_{it}}{W_{it_0}}\right) - ln\left(\frac{R_{it}}{R_{it_0}}\right) - g_{it_0 t}^A\right),$$

with $g_{it_0 t}^A = rate\ of\ growth\ of\ \ A_{it}^L/A_{it}^K$.

In theory the change-in-task content effect can be either negative or positive (or null), depending on whether the technology-induced labor displacement is larger or smaller than (or equal to) the technology-induced labor reinstatement. From this it follows that, to empirically highlight these two opposing forces, the change in task content has to be further decomposed in a displacement and reinstatement effect. Along with A-R, we do this by assuming that over a sufficiently long period (5 years) a sector can either adopt automation technologies or introduce new tasks, not both actions at the same time. On the grounds of this relatively strict assumption (in fact the 5-year window reduces its stringency), it is possible to single out the displacement and reinstatement effects from the negative/positive values of the moving average of the change in task content as follows:

$$Displacement_{t-1,t} = \sum_i \ell_{i,t_0} min\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} Change\ in\ task\ content_{i,\tau-1,\tau}\right\}$$

$$Reinstatement_{t-1,t} = \sum_i \ell_{i,t_0} max\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} Change\ in\ task\ content_{i,\tau-1,\tau}\right\}$$

Hence, a positive change in task content over a 5-year average is interpreted as a reinstatement of labor-intensive tasks, while vice versa a negative one means a displacement of labor in the task content of production.

A summary of the correspondences between each element of the model-based decomposition of the wage-bill change and the respective counterparts of the empirical decomposition is reported in Table 2.

Table 2. Decomposition of the economy-wide real wage bill: correspondence between model-based and empirical components

	Model-based decomposition	Empirical counterpart
Real wage-bill change	$dln\frac{W_t L_t}{P_t}$	$ln(W_t L_t/P_t) - ln\big(W_{t_0} L_{t_0}/P_{t_0}\big)$
-Productivity effect	$dlnY_t$	$ln\ Y_t - lnY_{t_0}$
-Composition effect	$\sum_i \frac{s_{it}^L}{s_t^L}\, d\chi_{i\,t}$	$ln\left(\sum_i \chi_{it} s_{i\,t}^l\right) - ln\left(\sum_i \chi_{i\,t_0} s_{it}^l\right)$
-Wage share change	$\sum_i l_{it}\, dln\, s_{it}^L$	$ln\left(\sum_i \chi_{i\,t_0} s_{i\,t}^l\right) - ln\left(\sum_i \chi_{i\,t_0} s_{i\,t_0}^l\right)$
---Markup effect	$\sum_i l_{it}\ dln\left(\frac{1}{m_{it}}\right)$	$\sum_i l_{it_0}\left[ln\left(\frac{1}{m_{it}}\right) - ln\left(\frac{1}{m_{it_0}}\right)\right]$
---Substitution effect	$\sum_i l_{it}(1-\sigma)(1 - m_{it}s_{it}^L)\left[dln\left(\frac{W_{it}}{A_{it}^L}\right) - dln\left(\frac{R_{it}}{A_{it}^K}\right)\right]$	$\sum_i l_{it_0}(1-\sigma)(1 - m_{it}s_{it_0}^L)\left[ln\left(\frac{W_{it}}{R_{it}}\right) - \ln\left(\frac{W_{it_0}}{R_{it_0}}\right) - g_{it_0 t}^A\right]$
---Change in task content	$\sum_i l_{it}\frac{1 - m_{it}s_{it}^L}{(1-\Gamma_{it})} dln\Gamma_{it}$	$ln\left(\sum_i l_{i\,t_0} s_{i\,t}^l\right) - ln\left(\sum_i l_{i\,t_0} s_{i\,t_0}^l\right) - \sum_i l_{it_0}\left[ln\left(\frac{1}{m_{it}}\right) - ln\left(\frac{1}{m_{it_0}}\right)\right] - \sum_i l_{it_0}(1-\sigma)(1 - m_{it}s_{it_0}^L)\left[ln\left(\frac{W_{it}}{R_{it}}\right) - \ln\left(\frac{W_{it_0}}{R_{it_0}}\right) - g_{it_0 t}^A\right]$
----Displacement effect	$\sum_i l_{it}\frac{1 - m_{it}s_{it}^L}{(1-\Gamma_{it})}\frac{dln\Gamma_{it}}{dI}$	$\sum_i \ell_{i,t_0} min\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} Change\ in\ task\ content_{i,\tau-1,\tau}\right\}$
----Reinstatement effect	$\sum_i l_{it}\frac{1 - m_{it}s_{it}^L}{(1-\Gamma_{it})}\frac{dln\Gamma_{it}}{dN}$	$\sum_i \ell_{i,t_0} max\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} Change\ in\ task\ content_{i,\tau-1,\tau}\right\}$

4. Data

Statistical sources

We apply the A-R decomposition methodology to the cases of France, Germany, Italy and Spain. The main source of data for this analysis is the EU-KLEMS database. This is a comprehensive source of harmonized measures providing information on growth, productivity, labor, capital formation and technological change at the industry level. To get the widest possible period of time, we gather information from the 2009 release (as updated in 2011) covering the period 1970-2007 and the latest version published in November 2019 covering the period 1995-2017. This way we observe a period of 47-years, from 1970 to 2017.

We consider the market economy, excluding public administration and real estate, as changes in the labor (capital) share of these sectors and their influence over the factor shares of the whole economy are, by construction, meaningless for economic interpretation (see Torrini, 2005, 2010, 2016)[2].

Given the different classifications adopted in the considered EU-KLEMS releases, the wage-bill decomposition has been conducted separately for two sub-periods (1970-1995 and 1995-2017). A link between the two sub-period decompositions has been made at the aggregate (market-economy) level in the year 1995.[3]

Additional statistical sources (OECD, AMECO and IFR databases) have been considered to gather the information necessary to implement the empirical testing of the model, and in particular to control the different variables (routine jobs, technology, globalization and trade-union density) that may influence wage-share and wage-bill changes. A more detailed description of all the datasets and the adopted variable transformations is available in Appendix 2.

Calibrations and approximations

Not all variables involved in the decomposition model are observable in statistical sources. In particular, we do not have information on the elasticity of substitution between labor and capital, the factor-bias of technological change and the markup, so that all these variables had to be appropriately calibrated and approximated on the grounds of specific assumptions.

As for the elasticity of substitution between production factors, reference is made to estimates available in the empirical literature. Evaluations appear quite heterogeneous across the analyzed countries and, also within the same country, across different studies/methodologies/periods (see Table 3). However, even with a high degree of variability, such estimates generally point to elasticities of substitution lower than 1 for the considered economies, with the partial exception of a couple of studies on Spain. All things considered, we choose to adopt an elasticity of substitution lower than 1 ($\sigma = 0.8$) as a baseline assumption common to all the four countries under examination. The adopted value coincides with the average of the elasticities provided by the most recent study available on this (Villacorta, 2020).[4]

[2] For the public sector, profit is null by definition because (gross) value added in public administration is given by wage bill plus depreciation on fixed assets. This implies that the share of capital in the whole economy will reduce, compared to that of labor, in the occurrence of an increase in supply of public services. As for real estate, the industry value added is directly imputed to the housing stock and labour does not really have a role as a production factor in it. Moreover, prices of real estate services strongly depend on investment choices and therefore can be quite far from the equilibrium ones. Based on these prices, it is usual to assess the imputed rents, which are accounted as part of household income even if no effective transaction takes place and which also contribute to defining the value added of the real estate sector.

[3] It follows from this procedure that the economy-wide wage-bill decomposition over the whole period 1970-2017 underlies a change in sector composition in 1995.

[4] It corresponds to the value adopted by A-R for the US as well.

Table 3. Overview of the estimates on elasticity of substituion σ available in the literature

Author/study	France	Germany	Italy	Spain
Villacorta (2020)	0.83	0.88	0.63	1.13
Muck (2017)				
Estimate A	0.319 - 0.371	0.400 - 0.834	0.360 - 1.539	0.423 -1.276
Estimate B	0.317 - 0.671	0.360 - 0.399	0.756 - 0.971	0.722 - 0.998
Baccianti (2013)	-	-	0.74	-
Saltari and Federici (2013)	-	-	0.66	-
McAdam and Willman (2004)	-	0.70 - 1.20	-	-
Bolt and Van Els (2000)	0.73	0.53	0.52	1.00
Rowthorn (1999)				
Estimate A	0.06 - 0.14	0.18 - 0.48	0.07 - 0.08	0.31
Estimate B	0.11 - 0.24	0.33 - 0.87	0.12 - 0.15	0.55
Koschel (1999)	-	0.436 - 1.22	-	-
Kemfert and Welsch (1998)	-	0.579 - 0.871	-	-

With regard to the bias of technological change, that is, the rate of growth $g^A_{it_0t} = A^L_{it}/A^K_{it}$, we assume along with A-R that all technological progress is labor augmenting, and so approximate $g^A_{it_0t}$ with the observed average rate of growth of (hourly) labor productivity in each sector over the relevant period. Note that considering all technological progress as labor augmenting leads to shrinking the relative price of effective labor, compared to other possible assumptions on technological bias. Since $\sigma < 1$, from this hypothesis follow both a possible overestimation of the role of the substitution effect in reducing the wage-share and, given the construction of the change in task content as a residual, a correspondent underestimation of the influence of technology in displacing the labor-intensive tasks contained in production processes. Hence, such an assumption on the labor-augmenting technical progress ends up representing a lower bound for the estimation of the change-in-task-content effect.

For the markup, following the literature (e.g. De Loecker, Eeckout, 2017), when measured as the ratio between output price and marginal costs (*c*), this variable can be expressed for the *i-th* sector as

$$m_{it} = \frac{P_{it}}{c_{it}} = \frac{h_{it}}{V_{it}}$$

Where h_{it} =output elasticity to variable inputs; V_{it}= share of variable inputs in gross output, so that $\frac{1}{V_{it}}$=$Gross\ Output/variable\ inputs$.[5]

While sector-level shares of variable factors in output, V_{it}, are observable and directly computable from available statistics, sector-level output elasticities, h_{it}, are not and have to be estimated. Yet both methodological issues and data constraints related to cross-country harmonization and comparability make such an estimation an awkward exercise (on this see Battiati et al. 2020). This problem can be partly dealt with in the dynamic setting that characterizes the decomposition exercise, assuming that the bulk of the markup change mainly reflects changes of the shares of

[5] The markup expression follows from the firm's cost minimization, allowing for both constant and increasing returns to scale.

variable-inputs share, with the output-elasticity change playing a minor role. It is mainly an empirical issue to verify how strong this assumption is. De Loecker and Eeckout (2017), assessing the relative importance of the markup components, find that during the period of a strong markup rise in the US, output elasticities to variable inputs indeed changed very little, while the change of the income share of variable inputs share explained almost the whole increase. It also has to be pointed out that national accounts statistics implicitly make this assumption when estimating aggregate and sector markup indexes (with respect to a base year) as a ratio between output price and average variable costs indexes. All in all, we choose to follow this approximation for the markup in the empirical application of the A-R (markup-adjusted) model to the European economies. Given national accounts information (provided by EU-KLEMS) on labor compensation and the value of intermediate inputs (the sum of which represents variable costs), the sector-level markup change in the decomposition exercise is computed as:

$$\Delta ln\ markup = \ \Delta ln\ [\ Gross\ Output/(Labor\ compensation + Intermediate\ Inputs)]$$

5. Decomposition results

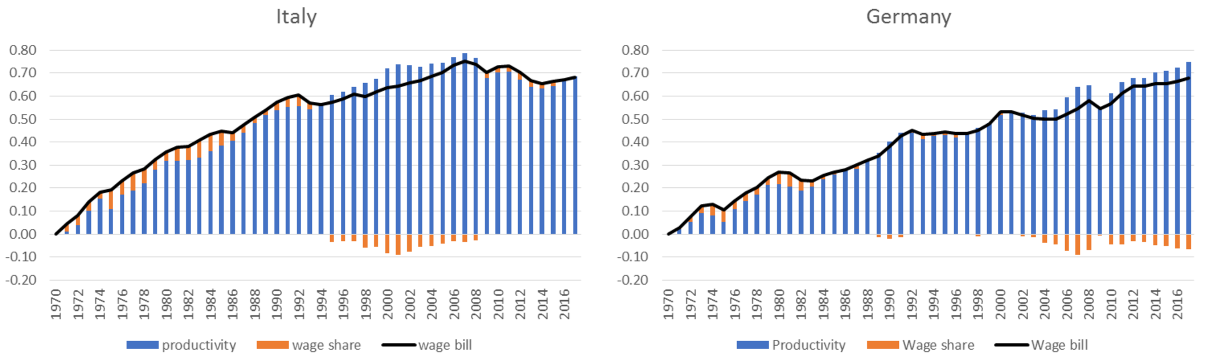
We apply the decomposition model illustrated in Section 3 to the wage bill of France, Germany, Italy and Spain over the period 1970-2017. For the period 1970-1995, we have data for 30 sector categories for the market economy classified according to the NACE1 classification; for the period 1995-2017 we have 34 sector categories according to the NACE2 revision. We conduct the decomposition separately for the two subperiods and then merge the aggregate results (which are in terms of log changes) in 1995 to get a complete view over the whole 47-year period. Hence, there are some underlying sector discontinuities behind the aggregate behaviors due to the break in 1995. We present the main results by steps.

The first step concerns the decomposition of the wage-bill change (in real terms and normalized by the population) into the productivity effect (per-capita real value added) and the economy-wide wage-share effect (gross of sector-composition shifts), that is

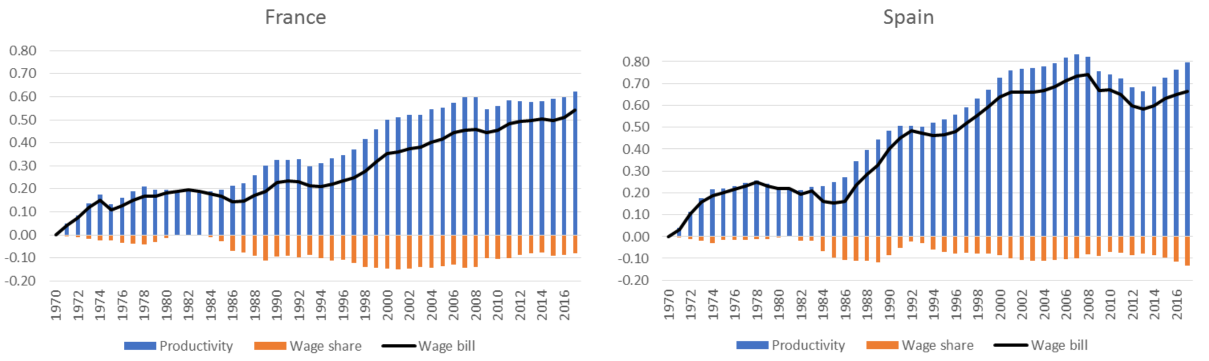
Wage-bill change = productivity effect + (economy wide) wage-share effect

This is shown in Graphs 1-4. As expected, the real (per-capita) wage bill is fundamentally driven by productivity developments. Misalignments between the two variables reflect wage share changes. The wage bill has decelerated in Germany, Italy and Spain since the early 1990s. It even declines in the latter two countries over the crisis period (2007-2013). France appears as an exception in this picture, with no appreciable slowdown. As for the wage bill components, Germany starts with an underperforming productivity growth and, correspondingly, a shrinking wage share in the early 2000s, that is, since the beginning of the monetary union. The Italian wage bill grows less than productivity, giving place to a falling wage share mainly between the early 1990s and the early 2000s. After the countercyclical rebound during the recession years (2008-2013), the wage share begins to weaken again. In France, as well as in Spain, the wage-share deterioration starts sooner than in the other two countries, being already detectable in the 1980s. Spain sees an intensification of the wage-bill squeeze in the post-recession years (2014-2017).

Graphs 1-4. Wage bill decomposition into productivity and wage share effects (log changes over 1970)



Own elaboration on EU KLEMS data



Own elaboration on EU KLEMS data

Wage-share changes are influenced by a variety of factors, with most of them considered in the A-R decomposition framework. In so far as labor market reforms affect the dynamics of wages relative to the rental price of capital, this is captured by the substitution effect. The latter is also influenced by technical change, if this is biased towards some specific production input. Deregulations and globalization may affect the degree of competition in product markets, and as such they produce markup shifts (Becker et al., 2013). Structural changes in the economic system (like tertiarization, aging, shifts in factors allocation) translate in change in sector composition. Moreover, as shown in the A-R framework, the opposing forces of automation and introduction of new labor-intensive tasks affect the wage share, inducing changes in the input-content of production tasks. These factors may be differently relevant in the considered countries in different periods. Labor-market reforms were realized in Germany notably after the fall of communism in order to respond to the rising competition from Eastern European countries (Dutsmann et al. 2014). The resulting wage moderation contributed to the wage share compression that materialized after the inception of the monetary union (De Nardis 2018). Similarly, wage moderation following labor-market reforms played a role in reducing the Italian wage share in the early 1990s. A trend that was reinforced by the privatization processes of relevant non-manufacturing sectors (Torrini 2005 and 2010). A markup squeeze because of the loss of competitiveness of the traded sectors facing growing international competition could have then contributed to the partial resumption of the wage share experimented in Italy in the years around 2005 (Torrini 2016). Wage moderation policies were put forward in France in the middle 1980s, after the wage shocks of the 1960s and early 1970s (Estevao and Nargis 2002). In Spain, profound institutional shifts from the end of the 1970s to 1986, when it became a member of the EU, substantially affected both the economic structure and the behavior of firms and workers. In general, sector composition changes and biased technological progress towards skilled workers (highly substitutive to unskilled ones) were common forces affecting the wage share dynamics in the considered countries (Arpaia et al. 2009). Automation-induced task changes were quite pervasive in European countries in the most recent decades (see Chiacchio et al. 2018 and the other studies surveyed in section 2).

All these factors enter the next step of the decomposition exercise, where the (economy-wide) wage share change is broken down as

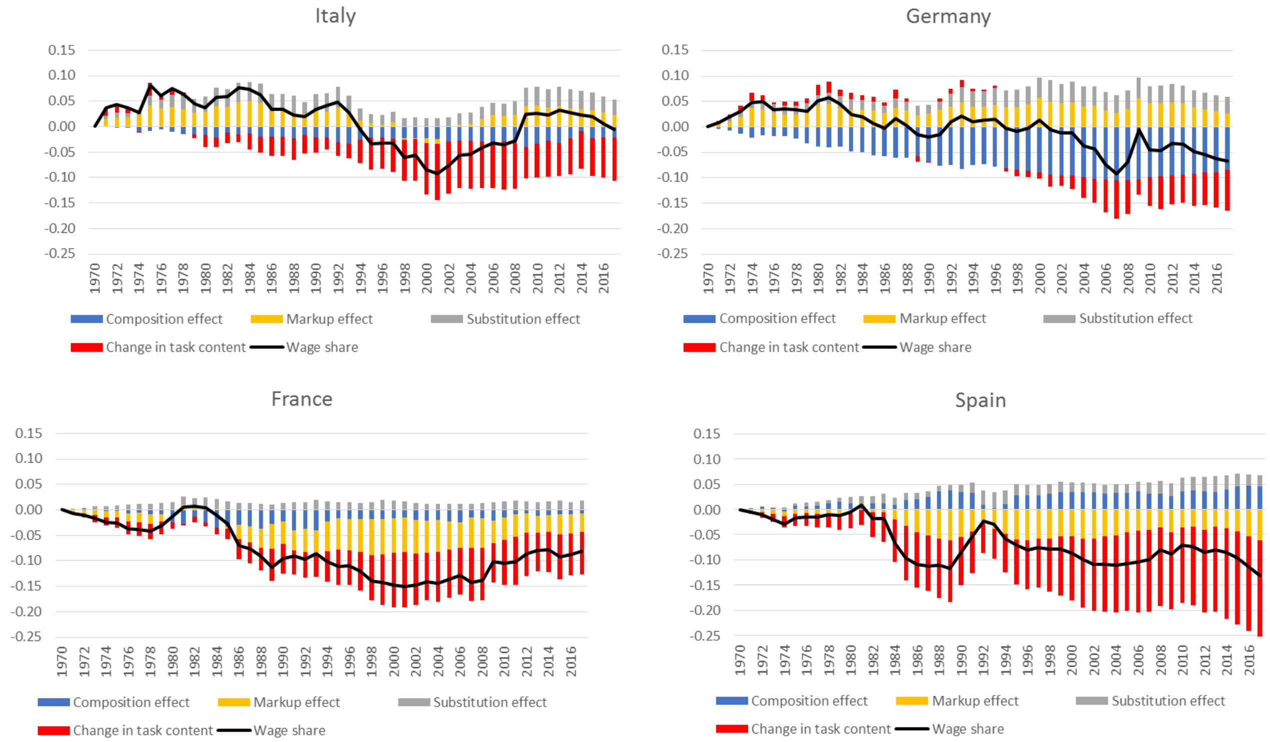
Wage-share change = composition effect + markup effect+ substitution effect + change-in-task-content effect

This decomposition is shown in Graphs 5-8. There are heterogeneities, but also common elements across the considered countries. First, along with the expectations coming from the A-R model, it can be noted that the deceleration of the substitution effect plays a relatively limited role in affecting the wage share. This occurs on the grounds of assumptions (labor augmenting technical change and substitution elasticity lower than 1) that tend to emphasize the role of wage moderation and technological progress in wage-share weakening. Another common element (with the exception of Spain) is the negative influence of sector composition on the wage share. Such an effect points to a change in composition of the market economy towards sectors characterized by lower wage shares. This is more pronounced in Germany, which is characterized by an increasing weight of productions that are capital intensive. In Italy a relative accentuation of this phenomenon can be observed in the first decade after 2000.

The markup effect exerts a different influence in Germany and Italy, on one hand, and France and Spain on the other. In the former two countries, markup compression has a tendency to sustain the wage share. In Italy this stops between the mid-1990s and the early 2000s (when privatization processes took place) to resume appreciably around 2005. Quite an opposite trend characterizes both France and Spain, with rising markups since the 1980s that explain a relevant fraction of the fall in wage share starting in that period.

Former effects do not exhaust all the possible factors affecting the wage share and, consequently, the wage bill. In the production-task-content framework, the unexplained portion of the wage share change is related to variations in the content of labor-intensive tasks of production processes. As Graphs 5-8 show, despite the differences of nationally specific stories, a common feature shared by the considered countries is the deterioration of the change-in-task-content component in the last 25-30 years. In Germany and Italy, the influence of such a component becomes relevant in the 1990s, after playing a marginal role in the former period. In Germany, the fall in labor-intensive task content materializes around 1995 and becomes determinant in the 2000s when, in addition to a constant negative composition effect, it leads to the wage-share compression observed in this period. In Italy, the change-in-task content effect contributes to the reduction of the wage share and thus to the lowering of the wage-bill dynamics below productivity between the early 1990s and the early 2000s and again in the most recent period (after 2013). A negative influence of the change in task content can already be detected in the 1980s in France and Spain; however, also in these countries the effect sensibly intensifies in the early 1990s, becoming the main driving factor of the wage-share change.

Graph 5-8. Wage share decomposition into *composition*, *markup*, *substitution* and *change in task content* effects (log changes over 1970)



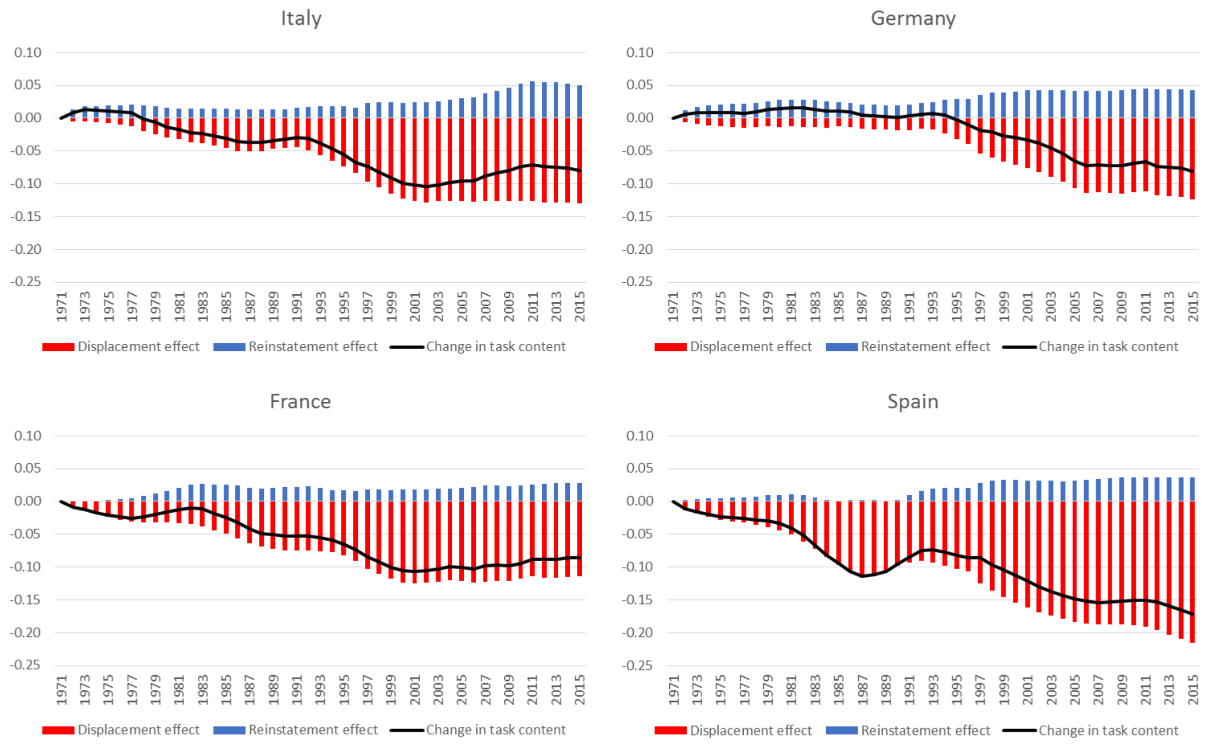
Own elaboration on EU KLEMS data

The last step of the decomposition concerns the breaking down of the change in task content into the labor displacement and reinstatement effects, as given by

$$\text{Change in task content} = \text{reinstatement effect} - \text{displacement effect}$$

This is shown in Graphs 10-14. As can be seen, the deterioration of the labor-intensive task content of production since the 1990s reflects an acceleration of the labor displacement effect in all the considered countries. There is also some intensification of the labor reinstatement effect (with the partial exception of France), but the introduction of new labor-intensive tasks is insufficient to offset the strengthening of the displacement effect experienced in this period.

Graph 10-14. Decomposition of *change in task content* into *displacement* and *reinstatement* effects
(log changes over 1970)

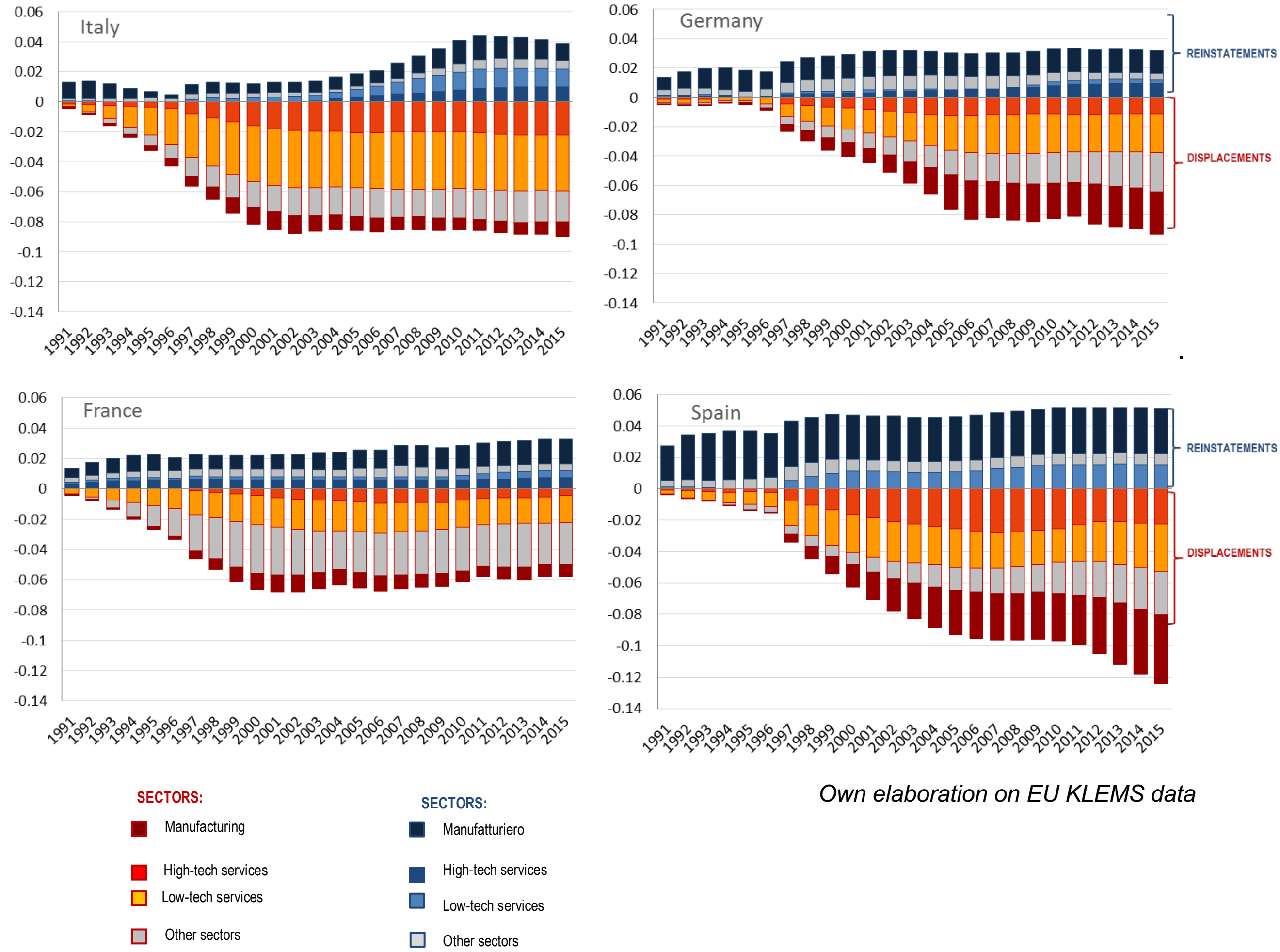


Own elaboration on EU KLEMS data

Given the different roles played by labor displacement and reinstatement in the examined countries, it is interesting to go deeper in the detection of the activities related to both these phenomena. This is shown in Graphs 15-19, where reinstatement and displacement effects are broken down into the contribution of a number of sectors, namely manufacturing, high-tech services, low-tech services and the rest.[6] In Italy, the intensification of displacement since the 1990s has mainly been driven by the reinforcement of this phenomenon in the low-tech services. These same sectors have contributed, beside the positive role exerted by manufacturing, to the rise of labor reinstatement since the early 2000s. A noticeable contribution to displacement coming from low-tech services is also observable in Germany and France. In Spain, these sectors also contribute to the reinstatement phenomena, analogously to the Italian experience. However, both in Germany and in Spain manufacturing is a more relevant contributor to both labor displacement and reinstatement, with the former effect prevailing over the latter. On the contrary, concerning Italian manufacturing, it is reinstatement that is larger than displacement. In France the stronger components in displacement are the residual sectors, as well as a relevant role played by the low-tech services.

[6] The grey bars in Graphs 15-19 show an aggregate obtained as a residual sum of all these remaining sectors (i.e. agriculture, mining, energy sector, waste management and constructions).

Graphs 15-19. Sectoral contributions to *displacement* and *reinstatement*, 1990-2017



Own elaboration on EU KLEMS data

To sum up the evidence of this section, despite national heterogeneities common elements arise from the wage-bill decomposition of the European countries. The deceleration of wage-bill growth in the last 30 years registered in Germany, Italy and Spain appears to be related to both productivity slowdown and adverse shifts in the task content of production, where the latter is connected to automation-induced labor displacement not adequately offset by the creation of new labor-intensive tasks. Even if no appreciable wage-bill deceleration is detectable in France, a similar deterioration of labor-intensive task content appears to take place there. Relevant contributions to displacement come from low-tech services in all countries. In Italy and Spain these sectors also contribute to reinstating new labor-intensive tasks. Manufacturing mainly exerts a reinstating effect in Italy, while displacement prevails over reinstatement in Germany and Spain. Residual sectors (including agriculture activities) have an important role in the French displacement experience.

It may be finally interesting to compare the obtained results with the US evidence reported by A-R. This comparison highlights a relatively less severe deterioration of the change in task content in the considered EU countries since the early 1990s. This partly depends on a less marked acceleration of labor displacement effects compared to the US. At the same time, the (although insufficient) strengthening of labor reinstatement observed in the analyzed European economies is absent in the US, where instead a slowdown of labor reinstatement pairs with the intensification of the displacement effect. Finally, the relevant role of displacement in the non-manufacturing sectors (particularly, in the low-tech services) characterizing the European countries is not matched by the US experience, where displacement appears mainly as a manufacturing phenomenon.

6. Displacement and technological change

In order to further investigate the decomposition results, we apply an econometric model to analyze the influence of a variety of factors, beside technology, which can affect the displacement effect, that is, the negative component of the change in task content of production. We consider three domains of interaction. We include first of all predictors for automation and technological change. We then consider the possible influence of globalization and international production networks. To these we finally add an explicit consideration of the labor-market institutional context; this is an indirect check of the A-R assumption, retained in our application, about firms' ability to stay on their labor demand schedule in a way that wage share is unaffected by possible rent bargaining.

Based on data availability, and matching the decomposition results in terms of sectoral detail and time period, we make use of different sources of information and model specification followed accordingly. Automation (*AT*) is alternatively measured by either the share of routine jobs at risk of automation (source OECD, Marcolin et al., 2016, 2019) or the operational stock of robots per industry (source IFR, 2020). Technological change is proxied by the variation in capital investments in ICT hardware (*HK*) and software (*SK*; the source for both kinds of investments is EU KLEMS). As for internationalization, the share of imported intermediate goods (*IG*) per each sector (source: OECD) is used to account for the influence of offshoring on production; and the weight of imports from China on domestic output (*CC*) is taken to factor in the Chinese competition per each industry (source: OECD). As for labor-market institution, unionization is included in terms of trade-union membership (*TU*) among all workers (source: OECD). Finally, we highlight the specificities emerged from the decomposition results in terms of differing sectoral contributions to the displacement and effects varying across the analyzed countries. We do this by means of two dummy variables: the first (*Man*), counting 1 per each manufacturing sector and null for the remaining; the second (*Spa*), taking value 1 for Spain only, in order to take account of the repercussions of the institutional changes that took place in this specific country.

A simple regression model was specified using the displacement effect as a dependent variable, and adding the mentioned predictors in subsequent stages. The empirical model in the complete form is:

$$Displ_{j,i} = \beta_1 \Delta ln\, AT_{j,i} + \beta_2 \Delta ln\, HK_{j,i} + \beta_3 \Delta ln\, SK_{j,i} + \beta_4 \Delta ln\, IG_{j,i} + \beta_5 \Delta ln\, CC_{j,i} + \beta_6 \Delta ln\, TU_{j,i} + Man + Spa + \varepsilon_{j,i}$$

where $j =$ countries and $i =$ sectors.

This is a cross-section equation where the left-hand variable (displacement effect) is the log change over the considered period. It is negative (as displacement enlarges it becomes more negative), so that the expected association with technology variables is also negative. Given that decomposition effects express delta logs on base year of the analyzed period (1995), the specification for the four countries in 2015 was chosen.[7] Table 4 summarizes the obtained results, where the share of routine jobs at risk of automation was used as a main proxy for this kind of technological change.

As we can see, the directionality of the relation between automation and displacement is always negative, and the coefficients acquire statistical significance when additional factors influencing change in tasks are included in the model. Particularly, this evidence points out that the displacement effect of technology cannot be reduced only to automation-exposed routine jobs. Equally relevant is the (negative) influence of the software component of technological capital (while the impact of the ICT hardware component is much less clear cut). Actually, this could be related to the displacement

[7] The sector-homogeneity constraint dictates the initial year (NACE 2 classification starts in 1995). The reason behind the choice of 2015 as the final year, instead of 2017, lies in the lack, by construction, of displacement values for 2016 and 2017. The estimation procedure of this effect, by means of a 5-year moving average, implies missing data for the first and the last two years of the time interval.

phenomena that took place in the service sector of the considered economies. As for the globalization domain, this analysis suggests that the international fragmentation of production chains, rather than the sole increase in foreign trade and competition, has an impact on displacement. However, the positive sign points to an overall competition-induced favorable effect that as such does not concur with technology in enlarging the displacement of labor-intensive tasks. Unionization does not appear to affect displacement significantly, although the introduction of this variable improves the statistical significance of the routine jobs coefficient. We interpret this evidence as an indirect confirmation of the assumption about the irrelevant influence of rent bargaining on wage share. Lastly, both considered dummy variables appear relevant for the specification and increase the overall explanatory power of the model. We interpret this latter finding as an indication that, contrary to the US case (see Acemoglu and Restrepo 2019), technology-induced displacement was not really a manufacturing phenomenon in the examined European countries considered as a whole (positive sign of the manufacturing dummy) and that, at the same time, relevant country-specific institutional changes had a significant impact on displacement (negative sign of the Spain dummy).

Table 4. Factors affecting displacement: results of regression model in the *routine jobs* specification

Measures of automation	(1)	(2)	(3)	(4)	(5)	(6)
Share of routine jobs at risk of automation	-0.3899	-0.3303	-0.4049	-0.4009 *	-0.6354 **	-0.5516 *
Std. Errors	*0.3052*	*0.2373*	*0.2344*	*0.2302*	*0.2961*	*0.2789*
K in Hardare components		-0.0092	-0.0567 **	-0.0716 *	-0.0419	0.0262
		0.0271	*0.0228*	*0.0392*	*0.0495*	*0.0459*
K in Software components		-0.0501	-0.1591 ***	-0.1553 ***	-0.1480 ***	-0.1450 ***
		0.0575	*0.0490*	*0.0484*	*0.0389*	*0.0378*
Measures of internationalization						
Offshoring of intermediates			0.0377	0.0442	0.0599 **	0.0790 ***
			0.0245	*0.0258*	*0.0253*	*0.0308*
Chinese import competititon			0.0251	0.0252	0.0151	0.0112
			0.0179	*0.0188*	*0.0173*	*0.0185*
Trade unions' density				0.0905	0.0461	0.0034
				0.1583	*0.1609*	*0.1046*
Manufacturing					0.0990	0.1473 **
					0.0622	*0.0688*
Country dummy						-0.1994 ***
						0.0661
Constant term	-0.0821	-0.0415	0.0328	0.0526	0.0530	0.0037
	0.0820	*0.1094*	*0.1339*	*0.1430*	*0.1229*	*0.1253*
N° observations	63	50	41	41	41	41
R^2	0.06	0.06	0.34	0.35	0.40	0.53

*** p < 0.01; ** p < 0.05; * p < 0.1 Robust s*tandard errors to control for heteroskedasticity, clustered by industry.*

Based on these results, the assumptions made about the significant impact that technological innovation (in terms of both automation and investment in software capital) has had on labor displacement seem confirmed. In order to delve deeper into this, a further stage of the econometric analysis envisioned the use of data on the adoption of robots per industry as the main proxy of automation (i.e. as an alternative variable for the *AT* term in the regression specification equation). Table 5 below shows the results obtained from this model replication.

Although the directionality of the effects seems confirmed, thus proving an inverse relation between automation and the task changes, in this case the coefficients fail to prove statistical significance and this specification of the *AT* variable cannot be considered sufficiently informative. Some considerations can still be made though. As happened with the previous estimate, the addition of internationalization predictors yields statistical significance to automation measures. While in Table 4 also the main proxy acquired relevance, here only the investments in software become highly significant, confirming the association that this kind of technological change has with displacement effects. As said before, this evidence seems to confirm that higher changes in task content of production came from the service sectors.

Table 5. Factors affecting displacement: results of regression model in the *robot* specification

Measures of automation	(1)	(2)	(3)	(4)	(5)	(6)
Robots, operational stock	-0.0054	-0.0046	-0.0063	-0.0066	0.0024	-0.0077
Std. Errors	*0.0078*	*0.0060*	*0.0085*	*0.0091*	*0.0120*	*0.0124*
K in Hardare components		0.0011	-0.0035	-0.0018	0.0025	0.0630
		0.0189	*0.0273*	*0.0428*	*0.0448*	*0.0486*
K in Software components		-0.0315	-0.0578 ***	-0.0584	-0.0384	-0.0340
		0.0274	*0.0303*	*0.0341*	*0.0294*	*0.0320*
Measures of internationalization						
Offshoring of intermediates			0.0322	0.0320	0.0436	0.0597
			0.0243	*0.0248*	*0.0304*	*0.0349*
Chinese import competititon			0.0135	0.0134	0.0064	0.0050
			0.0178	*0.0181*	*0.0212*	*0.0198*
Trade unions' density				-0.0115	0.0473	-0.0177
				0.1511	*0.1251*	*0.1385*
Manufacturing					0.0824	0.0790
					0.0859	*0.0817*
Country dummy						-0.1927 **
						0.0829
Constant term	-0.1974 ***	-0.1454 ***	-0.1520 ***	-0.1534 **	-0.2232 ***	-0.1937 **
	0.0223	*0.0324*	*0.0540*	*0.0595*	*0.1025*	*0.0858*
N° observations	81	64	51	51	51	51
R^2	0.01	0.03	0.11	0.11	0.13	0.25

*** p < 0.01; ** p < 0.05; * p < 0.1 Robust s*tandard errors to control for heteroskedasticity, clustered by industry.*

Also, some considerations must be borne in mind about the kind of performed task and the way automation makes an impact on the task variations. Although the International Federation of Robotics compiles its database on the penetration of industrial robots either by industry or by application, a combination of these two characteristics is not available. Despite the relevance of a sectoral analysis, it would certainly be useful to know also how robot application impacts the job tasks and better disentangle the intertwined relationship between the two, especially within a task-based framework as the one adopted in this study. A new robot application could indeed be either complementary (like "cobots", collaborative robots) or replace the human labor task it concerns. Moreover, the World Robotics dataset includes "multipurpose" robots only (Müller and Kutzbach, 2020), and so by definition excludes some specifically dedicated machines (e.g. equipment dedicated to loading/unloading of machine tools). More importantly, with the IFR dataset focused on *industrial* robots, and so not explicitly accounting for the *service* ones[8] (Müller et al., 2020), it risks

[8] For further details on the sectoral coverage of the robot dataset, see Appendix 2.

embedding a bias towards manufacturing, which among our considered sectors is the most likely to employ multipurpose industrial robots. Bearing in mind also what is shown by Graphs 15-19 about the sectoral disentangling of contributions to the task changes, it follows that the weak statistical significance of the relationship between the automation measured by the robot proxy and the displacement effect could be a result of an insufficient informative power of the chosen predictor itself. As a matter of fact, if the low-tech services were the more prominent contributors to changes in the four countries we considered, it could be difficult to grasp the magnitude of the displacement they engendered, making use of a variable that does not take them into account.

Furthermore, under the results presented in this chapter, a highly and persistently significant and negative relation between displacement and capital investments may suggest that such automation was more likely to be replacing in the case of software than hardware. This indeed seems supportive of the considerations expressed about the robot predictor as well, to the extent that software investments are more relevant in services than in other sectors.

In order to further expand on this subject, an additional specification of the model was tested, excluding all non-manufacturing sectors ex-ante (see Appendix 3). Besides the continuously significant negative influence of the software variable, investment in hardware components becomes relevant in this specification. Also, they both do so irrespectively of internationalization predictors this time. As regards robots, the results provided by this estimation are still insufficient to draw accurate conclusions, but they suggest that this relationship is less adverse than one could expect, and even less when looking at manufacturing alone. Moreover, international competition sounds more relevant for these industries than it appeared for the whole market economy. Finally, another validation comes from the latter specification, that is, the relevance of the country dummy, highlighting the institutional difference between the analyzed EU Member States and their labor markets.

7. Conclusions

This study has aimed to analyze the influence that technological changes have had on aggregate dynamics of the wage bill, the wage share and their components by focusing on the four main EU countries (France, Germany, Italy and Spain) over almost a 50-year period (1970-2017). In order to do so, we drew upon the decomposition framework elaborated by Acemoglu and Restrepo for the US case (2019). As showed, the empirical exercise applied to the market economy indicates that the wage-bill deceleration observed in these countries in the last decades was mainly productivity driven. Yet the emergence or intensification of a compression of the wage share induced the wage bill dynamics to fall short of the productivity deceleration for more or less prolonged periods. The reduction of labor-intensive tasks intensifying since the 1990s, concurrently with the latest wave of technological innovations, contributed appreciably to the compression of the labor share. Anyway, these negative effects look less pronounced when compared to those highlighted by A-R for the US.

A diminishing labor-intensive task content generally reflected a surge in labor displacement effects not sufficiently compensated by labor reinstatements through the creation of new tasks. A sectoral breakdown of these two opposing forces shows both common and country-specific features. Relevant contributions to displacement came from low-end service sectors in all countries. In Italy and Spain these sectors also contributed to reinstating new labor-intensive tasks. On the whole, this evidence allows us to underline that not only the intensity of the technology-induced displacement effects, but also the sectors where the compensating labor-reinstatement forces take place, is what actually matters for the labor share and wage-bill dynamics. Therefore, the net effect of the changes occurred in the task content of production differs from case to case. The magnitude of either these possible effects, or their combination, very much depends on the nature of the job-tasks to be carried out by workers and the kind of (displacing and reinstating) technologies being introduced. These elements are clearly relevant in determining the intensity of the productivity push induced by technological change.

Displacement was further investigated to allow for the possibility of this effect being correlated with additional influencing factors other than technology. The considered dimensions of analysis included: automatable employment shares and use of robots; other technology inputs such as capital investments in ICT hardware and software; globalization and shares of imported intermediate goods; and trade unions' membership. Empirical evidence provided by econometric modeling confirmed the negative correlation between displacement and technological innovations (particularly in the form of investment in software) and the related risks of automation for concerned human labor. Less indicative appeared the influence of industrial robots, probably due to the characteristics of the available statistics that are likely to underestimate automation in the service sector. The other considered domains (internationalization and intensity of trade-union membership) do not seem to influence this relationship's contribution to the enlargement of the displacement effect.

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Appendix

1. Wage bill decomposition

Here we show that the empirical decomposition of the wage bill approximates the theoretical model giving rise to the correspondences of Table 2 in the text.

Correspondence is straightforward for the productivity effect for which theory has a precise empirical counterpart, so we have:

$$ln\ Y_t - lnY_{t_0} = dlnY_t$$

Regarding the composition effect and the wage-share change, the empirical terms can be considered as approximations of the theoretical ones, since, as shown by A-R, the 1st order Taylor expansion of $ln\left(\sum_i \chi_{it} s^l_{i\,t}\right)$ around $ln\left(\sum_i \chi_{i\,t_0} s^l_{i\,t}\right)$ leads, for the composition effect, to:

$$ln\left(\sum\nolimits_i \chi_{it} s^l_{i\,t}\right) - ln\left(\sum\nolimits_i \chi_{i\,t_0} s^l_{it}\right) \approx \sum\nolimits_i \frac{s^L_{it}}{s^L_t}\, d\chi_{i\,t}$$

and the 1st order Taylor expansion of $ln\left(\sum_i \chi_{i\,t_0} s^l_{it}\right)$ around $ln\left(\sum_i \chi_{i\,t_0} s^l_{i\,t_0}\right)$ leads, for the wage-share change, to:

$$ln\left(\sum\nolimits_i \chi_{i\,t_0} s^l_{i\,t}\right) - ln\left(\sum\nolimits_i \chi_{i\,t_0} s^l_{i\,t_0}\right) \approx \sum\nolimits_i l_{it}\, dln\, s^L_{it}$$

To get the unspecified empirical counterparts of the components of the wage-share change (that is the markup effect, the substitution effect and the task-content change) in the *i-th* sector, equation (2) in the text is rewritten as:

$$s^l_{i\,t} = \frac{1}{m_{it}} \frac{1}{1+\frac{1-\Gamma_{it}}{\Gamma_{it}}(\rho_{it})^{\sigma-1}} \quad \text{where } \rho_{it} = \frac{W_{it}}{A^L_{it}}\frac{A^K_{it}}{R_{it}} \text{ and hence } s^l_{i\,t} = s^L(m_{it}, \rho_{it}, \Gamma_{it})$$

To get the components of $dln\, s^L_{it}$ apply the 1st order Taylor expansion of $lns^L(m_{it}, \rho_{it}, \Gamma_{it})$ around $lns^L\left(m_{it_0}, \rho_{it_0}, \Gamma_{it_0}\right)$, this approximately yields:

$$lns^L_{it} - lns^L_{it_0} = \frac{\partial lns^L\left(m_{it_0}, \rho_{it_0}, \Gamma_{it_0}\right)}{\partial lnm_{it_0}}\left(lnm_{it} - lnm_{it_0}\right) + \frac{\partial lns^L\left(m_{it_0}, \rho_{it_0}, \Gamma_{it_0}\right)}{\partial ln\rho_{it_0}}\left(ln\rho_{it} - ln\rho_{it_0}\right)$$
$$+ \frac{\partial lns^L\left(m_{it_0}, \rho_{it_0}, \Gamma_{it_0}\right)}{\partial ln\Gamma_{it_0}}\left(ln\Gamma_{it} - ln\,\Gamma_{it_0}\right)$$

Hence the parameter multiplying $\left(lnm_{it} - lnm_{it_0}\right)$ is *-1*, which means that the parameter multiplying $\left(\ln\left(\frac{1}{m_{it}}\right) - \ln\left(\frac{1}{m_{it_0}}\right)\right)$ is *1* as in the theoretical model.

As for the relative factor-price change, identified by the ρ term, in the *i-th* sector we have:

$$\frac{\partial lns^L\left(m_{it_0}, \rho_{it_0}, \Gamma_{it_0}\right)}{\partial ln\rho_{it_0}} = \frac{1}{s^L_{it_0}} \frac{-1}{\left[m_{it_0}\left(1+\frac{1-\Gamma_{it_0}}{\Gamma_{it_0}}\left(\rho_{it_0}\right)^{\sigma-1}\right)\right]^2} m_{it_0} \frac{1-\Gamma_{it_0}}{\Gamma_{it_0}}(\sigma-1)\rho^{\sigma-2}_{it_0}\rho_{it_0}$$
$$= -s^L_{it_0} m_{it_0} \frac{1-\Gamma_{it_0}}{\Gamma_{it_0}}(\sigma-1)\rho^{\sigma-1}_{it_0} = \left(1 - m_{it_0} s^L_{it_0}\right)(1-\sigma)$$

It follows that the parameter multiplying $(ln\rho_{it} - ln\rho_{it_0})$ is $(1 - m_{it_0}s^L_{it_0})(1-\sigma)$ which coincides with the parameter of the *substitution* effect of the theoretical model.

Regarding the change in task content in the *i-th* sector we have:

$$\frac{\partial lns^L(m_{it_0},\rho_{it_0},\Gamma_{it_0})}{\partial ln\Gamma_{it_0}} = \frac{1}{s^L_{it_0}} \frac{-1}{\left[m_{it_0}\left(1+\frac{1-\Gamma_{it_0}}{\Gamma_{it_0}}\left(\rho_{it_0}\right)^{\sigma-1}\right)\right]^2} m_{it_0}\rho^{\sigma-1}_{it_0}\left(-\frac{1}{\Gamma_{it_0}} - \frac{1-\Gamma_{it_0}}{\Gamma^2_{it_0}}\right)\Gamma_{it_0} =$$
$$-s^L_{it_0}m_{it_0}\rho^{\sigma-1}_{it_0}\left(-\frac{1}{\Gamma_{it_0}}\right)=\frac{1-m_{it_0}s^L_{it_0}}{1-\Gamma_{it_0}}$$

Hence the parameter multiplying $(ln\Gamma_{it} - ln\,\Gamma_{it_0})$ is $\frac{1-m_{it_0}s^L_{it_0}}{1-\Gamma_{it_0}}$ coinciding with the one of the *change-in-task-content* of the theoretical model.

2. Data treatment for decomposition exercise

As mentioned in the text, the main statistical source for this work was the EU KLEMS. Although many variables were taken as such from the original database, some estimates were needed - for example, in the case of the variable CAP, capital compensation, when its values were lower than zero. With this occurrence being possible because the original variable is obtained as a residual of VA (value added) minus LAB (labor compensation), it created a distortion in our analysis when used to calculate delta logs on negative values in base year. While in the EU KLEMS methodology literature (Timmer et al., 2007) a suggested solution for this is to replace negative values with zeros, we could not apply it to solve our specific problem and we chose to intervene directly on the signs of the estimated effect, which starting with negative values produced delta logs of a counterintuitive directionality.

Table A1. Descriptive statistics of variables used in the decomposition exercise

Variable	Source	n° obs.	Mean	Std. Dev.	Min	Max
Value Added	EU KLEMS (va)	3,128	30241	34972	-751	319354
Labor compensation	EU KLEMS (lab)	3,128	21491	26411	-403	241751
Capital compensation	EU KLEMS (cap)	3,128	8750	10649	-7568	98733
Labor services	EU KLEMS (lab_qi)	3,128	101.4	19.5	13.6	275.5
Capital services	EU KLEMS (cap_qi)	3,128	95.3	21.0	27.4	369.9
Gross output	EU KLEMS (go)	3,220	137471	423585	1518	4708708
Intermediate inputs	EU KLEMS (ii)	3,220	78718	242172	297	2609507
Price index for labor	own elaboration on EU KLEMS	3,128	218.2	268.6	-5.0	2101.2
Price index for capital	own elaboration on EU KLEMS	3,128	95.0	122.4	-74.9	1545.1
Labor productivity	own elaboration on EU KLEMS	3,128	0.16	0.30	-1.62	1.92
Sigma	own elaboration on literature	3,128	0.87	0.18	0.63	1.13

In the case of missing data, they have been estimated by referring to the closer variable available (as in the case of LAB_QI, labor services, which were computed based on the distribution of H_EMP, n° of hours worked by employed persons per sector). When no directly related variable was available as basis for the estimate (as in the case of CAP_QI, capital services), we assumed that sub-sector values could be proxied by main reference sectors.

3. Econometric model: variables and validation

The indicator used to quantify the share of routine jobs at risk of automation was estimated by combining two OECD references (Marcolin et al., 2016 e 2019) on this issue. Matching the national and sectoral information provided by the two, we obtained a national indicator with an industry level detail referred to the early 2010s. In particular, sectoral shares of jobs at (both medium and high) risk of automation available for the whole total of OECD members were reallocated to the four analyzed countries based on the percentage incidence that routine jobs have per each of the considered countries with respect to the OECD total. In the econometric estimate we consider the level of this variable. In doing so, we assume a substantial stability of the share of automation-exposed routine jobs in each sector/country over the considered period.

The variables on investments in hardware and software were obtained from the information on capital stock net available in the EU KLEMS Capital Accounts. We selected the *computing* and *communications equipment* together, along with the *computer software and databases* statistics, and calculated their variations over the period analyzed by the model. We take the log variations of these variables over the period 1995-2015.

Data on penetration of robots were instead taken from the World Robotics 2020 database, compiled by the International Federation of Robotics, referring to the operational stock measure per industry. Given the use of ISIC rev.4 to classify the sectoral distribution of robots in this dataset, a conversion to our NACE rev.2 was needed before use. Considering also the lack of information on services, we followed the strategy (common to previous similar studies, e.g. Acemoglu and Restrepo, 2017) of reallocating the “unspecified” codes to missing industries. In particular, in order to approximate the underlying sectoral distribution useful as a reference parameter, we used the volumes of gross fixed capital formation per other machinery and equipment (Iq_Omach) available in the EU KLEMS Capital accounts. We reassigned the 90 code “All other non-manufacturing branches” among service sectors first, and the 99 code “Unspecified” across all sectors next. This way we were able to obtain a full matrix to match our estimates dataset. Finally, we considered the obtained values of robot units per industry as delta logs over the period 1995-2015.

As for internationalization, the OECD “Input-Output Intermediate Import Ratio” indicator was used to take into account the weight of imported intermediate goods into domestic production. With it being available for three periods (mid 1990s, early 2000s, and mid 2000s) we used the delta log between the third and the first one to cover the time interval considered by the model. The log variations in sectoral imports from China (expressed as share of the domestic gross output) were instead used to approximate foreign trade competition.

To take into account the institutional context, data were taken from the OECD “Employment Protection Legislation” database: within the Trade Union dataset, the number of union members was taken to calculate the ratio of the overall number of employed persons (while the OECD *trade union density* indicator is obtained with respect to employees only). With these statistics available at the economy wide level, our calculation has been weighted based on sectoral employment shares. We consider the log variation of this variable over the period 1995-2015.

Table A2. Descriptive statistics of variables used for econometric model

Variable	Source	n° obs.	Mean	Std. Dev.	Min	Max
Displacement	own elaboration on EU KLEMS	3,128	-0.09	0.16	-1.44	0.00
Routine Jobs at risk of automation	own elaboration on OECD	2,484	0.34	0.13	0.12	0.60
K investments in Hardware	own elaboration on EU KLEMS	2,558	0.45	0.70	-1.81	3.51
K investments in Software	own elaboration on EU KLEMS	2,550	0.50	0.52	-0.74	3.65
Robots	own elaboration on WRD	3,082	2.48	2.52	-5.21	10.21
Intermediate goods	own elaboration on OECD	2,806	0.19	0.49	-2.20	2.20
Chinese competition	own elaboration on OECD	2,493	0.97	1.26	-4.22	6.07
Trade union's density	own elaboration on OECD	3,128	-0.07	0.17	-0.55	0.18

As explained in the text, the estimated model was applied with additional specifications in order to check and validate its meaningfulness. Table A3 and A4 summarize the results obtained using the penetration of robots as the main automation proxy, estimating the model either on the whole market economy or on manufacturing sectors only.

Table A3. Factors affecting displacement: results of regression model in the *robot* specification, manufacturing

Measures of automation	(1)	(2)	(3)	(4)	(5)
Robots, operational stock	-0.0020	-0.0027	0.0060	0.0167	0.0222 **
Std. Errors	*0.0101*	*0.0084*	*0.0091*	*0.0114*	*0.0085*
K in Hardare components		-0.0679 ***	-0.0653 **	-0.1289 ***	-0.0009
		0.0217	*0.0246*	*0.0395*	*0.0277*
K in Software components		-0.1171 ***	-0.1092 ***	-0.0994 ***	-0.0910 ***
		0.0321	*0.0306*	*0.0256*	*0.0141*
Measures of internationalization					
Offshoring of intermediates			0.1549 **	0.1312 *	0.1348 ***
			0.0647	*0.0672*	*0.0432*
Chinese import competititon			0.0514 ***	0.0371 **	0.0434 ***
			0.0131	*0.0165*	*0.0094*
Trade unions' density				0.3403 *	0.0592
				0.1647	*0.1019*
Country dummy					-0.2389 ***
					0.0466
Constant term	-0.1865 ***	-0.0560	-0.1944 ***	-0.0910	-0.1499 ***
	0.0234	*0.0377*	*0.0496*	*0.0529*	*0.0355*
N° observations	32	28	26	26	26
R^2	0.00	0.22	0.51	0.61	0.84

*** p < 0.01; ** p < 0.05; * p < 0.1 Robust s*tandard errors to control for heteroskedasticity, clustered by industry.*

Finally, the main model specification presented in the text was tested to exclude endogeneity of predictors, as well as to check the conditions of linearity and verify the suitability of considered variables. As for the latter, a Ramsey *Regression Equation Specification Error Test* (RESET test) was applied, obtaining a result of no omitted variables. Also, a *variance inflation factors* test did not detect multicollinearity among specified predictors. To control for heteroskedasticity, robust standard errors were clustered per industry.

As for endogeneity, first of all a graphical analysis of the residuals was checked, with it being possible in principle that the *change in task content* itself determines some variations in capital investments over new technologies, or offshoring, or unionization. Moreover, bivariate simple regressions between the residuals of the model and each predictor were tested. The results, excluding any statistical significance of these relationships, are presented in the following table.

Table A4. Regressions of residuals on predictors

	Routine jobs at risk of automation	**K investments in Hardware**	**K investments in Software**	**Trade Unions**	**Intermediate goods**	**Chinese competition**	**Manufacturing**	**Country dummy**
Coefficients	0.185	0.020	0.012	0.091	-0.046	-0.018	-0.082	-0.028
Std. Errors	*0.141*	*0.018*	*0.028*	*0.074*	*0.028*	*0.012*	*0.033*	*0.043*
P>t	0.196	0.249	0.681	0.223	0.101	0.133	0.015	0.511
R^2	0.024	0.019	0.003	0.021	0.039	0.032	0.083	0.006
N° of obs.	71	71	71	71	71	71	71	71

Graph A1. Graphical analysis of residuals