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New technologies and jobs in Europe

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Abstract

We examine the link between labour market developments and new technologies such as artificial intelligence (AI) and software in 16 European countries over the period 2011-2019. Using data for occupations at the 3-digit level in Europe, we find that on average employment shares have increased in occupations more exposed to AI. This is particularly the case for occupations with a relatively higher proportion of younger and skilled workers. This evidence is in line with the Skill Biased Technological Change theory. While there exists heterogeneity across countries, only very few countries show a decline in employment shares of occupations more exposed to AI-enabled automation. Country heterogeneity for this result seems to be linked to the pace of technology diffusion and education, but also to the level of product market regulation (competition) and employment protection laws. In contrast to the findings for employment, we find little evidence for a relationship between wages and potential exposures to new technologies.

Keywords: artificial intelligence, employment, skills, occupations

JEL codes: J23, O33

Non-technical summary

Recent advancements in AI (Artificial Intelligence)-enabled technologies have revived the debate about the impact of technologies on jobs. Historically, waves of innovation have been associated with anxiety about the future of jobs and concerns about labour becoming redundant. However, the historical record suggests that the potential negative effects of technology on employment have been counterbalanced by increases in productivity and creation of new tasks. It remains an open question if the same can be expected from AI-enabled technologies. In this paper we provide evidence on the links between AI, employment shares and relative wages by occupations at the 3-digit level in 16 European countries during the period 2011-2019. We also explore how this association varies across skills and age groups. We compare findings for AI - which is a new general purpose technology, experiencing fast growth innovation - with those for software, which is a well-established technology. To measure AI, we use the occupational indices provided by Webb (2020) and Felten et al. (2018). Both measures, originally developed for the US, capture the exposure to AI for different occupations. The Webb measure calculates this exposure based on the tasks comprising an occupation, while the Felten et al. measure quantifies the exposure to AI based on the abilities required for an occupation. We interpret both measures as proxies to potential AI-enabled automation. Our theoretical framework is based on the task-based framework by Acemoglu and Restrepo (2018) and Webb (2020) . New technologies impact overall employment and aggregate wages, as well as the wage and employment distribution, through various channels. First, new technology developments destroy jobs because they automate tasks (displacement effect). Second, they might complement human labour, thereby increasing productivity and indirectly resulting in more jobs due to an increase in demand for products of some firms (productivity effect). Third, a combination of both effects: some tasks and jobs being replaced but new ones being created through innovation (the so-called reinstatement effect). Thus, it is not clear whether new technologies would necessarily lead to an overall loss in aggregate employment. Our results suggest a positive association between AI-enabled automation and changes in employment shares in the pooled sample of European countries, regardless of the exposure measure used. However, we do not obtain a clear signal for the impact on wages. The positive impact of AI-enabled automation on employment is mostly driven by younger workers and high-skilled workers. This is in line with the Skill Biased Technological Change theory. For Software, we did not find a statistically significant impact across skill groups and thus we could

not corroborate previews findings of software having a negative impact on medium-skilled workers. As Software is a mature technology, its impact on the structures of skills may have been realised before this period, although the results are very heterogeneous across countries. The positive impact of AI-enabled technologies on employment holds across countries with only a few exceptions. However, the magnitude of the estimates largely varies across countries. Country heterogeneity seems to be linked to the pace of technology diffusion and education, but also to the level of product market regulation (competition) and employment protection laws. Results should however be taken with caution as these technologies are still in their early stages

1 Introduction

Skill Biased Technological Change (SBTC) and Routinisation are the leading theories explaining the effects of technology on the labour market. Both theories point to heterogeneous impacts of technology across the skill distribution that support employment and wages of high skilled workers.[1] SBTC explains drifts of labour demand towards high skilled workers triggered by technology developments. This monotonic relation between skills and labour demand was the initial source of the rise in inequality that started in the late 1970s (see Autor et al. (1998), Autor and Katz (1999), and Acemoglu (2020) for a summary). Starting in the early 1990s, wage and job polarisation accelerated as many medium-skilled workers, mostly in routine-intensive jobs, were displaced. This posed a puzzle to the SBTC theory and gave rise to what is known in the literature as the Routinisation theory, which established that the rise in automation leads to a decline in the demand for routine tasks performed by medium-skilled workers, and an increase in the demand for non-routine tasks, performed by workers at the top and the bottom of the wage distribution (Autor et al. 2003). A large body of the empirical literature confirmed these patterns (e.g. Goos and Manning 2007, Acemoglu and Autor 2011, Autor and Dorn 2013, Goos et al. 2014, Cortes et al. 2017, vom Lehn 2020).

Regarding technological change, the more recent period since around 2010, on which we focus in this paper, is characterised by the emergence of artificial intelligence (AI) breakthroughs, including advancement in robotics, supervised and unsupervised learning, natural language processing, machine translation, or image recognition among many other activities, that enable automation of human labour in non-routine tasks, both in manufacturing but also services (e.g. medical advice or writing code). AI is thus a general purpose technology that could affect work in virtually every occupation. It is experiencing fast growth and diffusion (Agrawal et al. 2018) and has revived the debate about the potential impact of technologies on jobs (see for example Ford 2015, Frey and Osborne 2017, Susskind 2020 and Acemoglu and Restrepo 2020b).

Automation, including AI-enabled automation, impacts overall aggregate employment and aggregate wages, as well as the wage and employment distribution, through various direct channels. First, new technology developments destroy jobs because they automate tasks (displacement effect). Second, they might complement human labour, allowing for a more flexible allocation of tasks and increasing productivity (productivity effect). This, in turn, contributes

[1] However, these recent patterns cannot be generalised to all waves of innovation and technological developments since the industrial revolution as discussed in Goldin and Katz (1998).

to increased demand for labour in non-automated tasks. Third, a combination of both effects: some tasks and jobs are being replaced but new tasks and jobs are created either because of innovation, or because old technologies become so cheap that their demand starts rising (the so-called reinstatement effect). In addition, there are several indirect channels that act across industries. The most obvious example is the existence of spillover effects, either by increases in productivity transmitted across industries through the intermediate inputs or by increases in incomes that yield higher aggregate demand. By enabling automation of non-routine tasks, typically performed by high skilled workers, AI would give a new aspect to the SBTC theory, which was dominant before the advent of Routinisation for explaining drifts of labour demand towards high skilled workers.

Waves of automation and new technology have usually been accompanied with anxiety about the future of jobs and with concerns about labour becoming redundant. Even though the historical record suggests that such concerns are often overstated (Autor, 2015). Thus, it is not surprising that there is an expanding literature that focuses on the impact of technology on aggregate employment and wages. So far, the existing evidence on the overall effect of new technologies on employment is mixed. Much of the recent literature, focusing on the US, estimates that automation has a positive net effect on the total number of jobs, but tends to reduce the number of low-skill jobs. In contrast, some recent work for France highlights that the introduction of automation can have a positive effect also on the employment of unskilled industrial workers. The benefit for low-skilled workers is mostly driven by aggregate productivity gains in the French manufacturing sector that are shared between workers and firm owners (Aghion et al., 2023).

To assess the the potential impact of AI-enabled automation on labour markets, measures of AI are required. Recent papers have proposed several indicators of the progress of AI with a view on its potential labour market effects. Felten et al. (2018) and Felten et al. (2019) create a measure, the AI Occupational Impact (AIOI), that links advances in specific applications of AI to workplace tasks and occupations. Using this measure, they provide evidence that, on average, occupations impacted by AI experience a small but positive change in wages, but they do not identify any change in employment. Webb (2020) constructs a measure of the exposure of tasks and occupations to AI, as well as to robots and software, using information on job task descriptions and the text of patents. He finds that even if substantial uncertainty about its impacts remains, AI, in contrast to software and robots, is directed at high-skilled tasks.

Acemoglu et al. (2022) use the occupational measures provided by Webb (2020) and Felten et al. (2018) and Felten et al. (2019) as well as the Suitability for Machine Learning (SML) index by Brynjolfsson et al. (2018), and conclude that the impact of AI is still too small relative to the scale of the US labour market to have had first-order impacts on employment patterns.

With this paper we contribute to this literature by exploring the links between AI and employment shares and relative wages by occupations at the 3-digit level in 16 European countries during the period 2011-2019. We also describe how this association varies across skills and age groups, and shed some light on the prevalence of the SBTC theory compared to the Routinisation theory. To measure AI, we use the occupational indices provided by Webb (2020) and Felten et al. (2018). Both measures, originally developed for the US, capture the exposure to AI for different occupations. The Webb measure calculates this exposure based on the tasks comprising an occupation, while the measure by Felten et al. quantifies the exposure to AI based on the abilities required for an occupation.

We interpret both measures as proxies to potential AI-enabled automation. Our results suggest a positive association between AI-enabled automation and changes in employment shares in the pooled sample of European countries, regardless of the proxy used. According to the AI exposure indicator proposed by Webb, on average in Europe, moving 25 centiles along the distribution of exposure to AI is associated with an increase of the sector-occupation employment share of about 2.6%, while using the measure by Felten et al. the estimated increase of the sector-occupation employment share is 4.3%. The positive association supports the idea that in Europe, automation enabled by the adoption of AI would not result in lower aggregate employment, and contrasts somehow with the findings for the US discussed above.

Assessing patterns within specific population groups and countries, we do not find any significant changes in employment shares that are associated with potential exposure to AI for the low and medium skill terciles. However, for the high skill tercile, we find a positive and significant association: moving 25 centiles up along the distribution of exposure to AI is estimated to be associated with an increase of the high skilled sector-occupation employment share of 3.1% using Webb's AI exposure indicator, and of 6.6% using the measure by Felten et al. These findings show that the positive relationship between AI-enabled automation and employment growth uncovered for the pool of countries is driven by jobs that employ high skilled workers, in line with the SBTC theory. Across countries, one expects that the impact of these technologies will vary depending on their distribution of employment across sectors and occupations, which are differently exposed to the technologies. Indeed, while the relationship between AI and employment tends to be positive also at the country level, we find heterogeneity in the magnitude of the estimates. This heterogeneity is related to the pace of technology diffusion and education across sectors and occupations, but also to the level of product market regulation (competition) and employment protection laws.

To shed light on the possible prevalence of the Routinisation theory, we perform similar analyses for software-enabled automation using the occupational measure of software exposure by Webb (2020). Our findings are somewhat at odds with the seminal work on the effect of digital technologies on wages (Krueger 1993 and Autor et al. 1998). The relationship between software exposure and employment changes is heterogeneous across countries, but null for the pooled sample, and we do not identify evidence of software replacing routine medium skill jobs.

Overall, our results indicate a mildly positive impact of AI on the labour market, although it is too early to foresee the scope and applicability of the newest wave of AI technologies and our analysis is silent on aggregate effects. One plausible interpretation of our findings is that the negative effect on employment is far less sizable than the most pessimistic outlook for AI driven job destruction often emphasised in popular narratives. Moreover, the positive association between potential exposure to AI and employment among young and skilled workers suggests that accumulation of human capital and increases of labour supply at the top of the skill distribution continue to be the way to accommodate new technologies without employment losses, as under the SBTC theory.

The rest of the paper is organised as follows: Section 2 presents a simple model to illustrate the potential impact of technology in the labour market. Section 3 describes the data used. Section 4 offers some descriptive statistics. Section 5 discusses the empirical strategy and the results. Section 6 concludes.

2 Conceptual Framework

This section presents a simple conceptual framework to illustrate the channels through which technological change affects employment shares and relative wages by occupation using a simple task-based framework, based on Acemoglu and Restrepo (2020a) and as extended in Webb (2020) to consider variation by occupation.

Occupations, $o_{i,t}$ $i \in (1, I_t)$, are combinations of tasks $j \in (1, J_i)$ that produce intermediate inputs used in the production of the final good y_t:

$$y_{i,t} = \sum_{i=1}^{I_t} \left[\alpha_i o_{i,t}^{\rho} \right]^{1/1-\rho} \tag{1}$$

with I_t being the number of occupations, α_i the weight of occupation i in the production of the final good, and $\rho/(1-\rho)$ the elasticity of substitution among occupations.

Each task can be performed either by a combination of human labour and "machines" or only by "machines" if the task is fully automated when AI enables total substitution of human labour in such tasks.

An occupation fully automated $i \in A_t$ can be performed without human labour. In such case:

$$o_{i,t} = \sum_{j=1}^{J_i} \beta_{i,j,t} \lambda_t M_{i,j,t} \tag{2}$$

where J_i denotes the (time-invariant) number of productive tasks at each moment in time t that are performed within occupation i, $\beta_{i,j,t}$ is the weight of task j in occupation i at time t, and λ_t denotes the relative productivity of machines versus labour.

Labour is employed in the rest of occupations $i \in I_t - A_t$ which need to be performed using machines ($M_{i,j,t}$) and labour ($L_{i,t}$):

$$o_{i,t} = L_{i,t}^{\mu_i} \left[\sum_{j=1}^{J_i} \beta_{i,j,t} \lambda_t M_{i,j,t} \right]^{1-\mu_i} \tag{3}$$

$\mu_i \in (0,1)$ controls input shares in occupations of the labour intensive sector. The relative price of machines is q_t. Supply of labour and machines is predetermined.

Full automation is feasible for a given occupation when technology is more productive than labour, i.e., $\lambda_t > q_t/W_{i,t}$, where $W_{i,t}$ is the wage paid to labour in occupation i at time t. For simplicity we assume that innovation is exogenous and that the size of the total set of occupations, I_t, and of the set of automated occupations, A_t, grows at the same (exogenous) rate n, and the relative price of machines, q_t, is also exogenous.[2]

Given the simple Cobb-Douglas structure of the production functions, it is straightforward to derive the labour demand equation for occupations $i \in I_t - A_t$. Since:

$$\frac{W_{i,t} L_{i,t}}{q_t \phi_{i,t}} = \frac{\mu_i}{1-\mu_i} \tag{4}$$

[2]For a model with endogenous innovation and automation, see Basso and Jimeno (2021).

with

$$\phi_{i,t} = \sum_{j=1}^{J_i} \beta_{i,j,t} \lambda_t M_{i,j,t} \tag{5}$$

then,

$$L_{i,t}^d = \left[\frac{\mu_i q_t}{(1-\mu_i) W_{i,t}} \right]^{1-\mu_i} o_{i,t}^d \tag{6}$$

where $o_{i,t}^d$ is demand for occupation i at time t.

As for wages, we assume sectoral wage bargaining between an occupation-wide employer federation and an occupation-wide union. The employer federation and the union care about the aggregate surplus workers covered by the wage agreement. Let γ_i and δ_i, respectively, be the cost for the employer federation of not reaching an agreement and the payoff to workers in such a case in occupation i, and let κ_i be the union bargaining power in occupation i. Then under most general assumptions (see Jimeno and Thomas 2013), the bargaining wage is:

$$W_{i,t} = \kappa_i \left[\frac{o_{i,t}}{L_{i,t}} + \delta_i + \gamma_i \right] \tag{7}$$

Hence, the wage structure is determined by average productivity in each occupation, and by occupation-specific union bargaining power and negotiation costs. Notice that this bargaining configuration carries two features of wage determination that will be relevant for discussing the impact of new technologies on wages: labour market segmentation (since productivity and union bargaining power vary across occupations) and compensating differentials (which may be discussed referring to occupation-specific negotiation costs).

Equations (6) and (7), together with the evolution of the fully automated and labour intensive occupations, illustrate the potential impacts of new technologies on employment shares and wages. These impacts have been grouped in the literature in three types of effects: productivity, substitution, and reinstatement effects. Progress in the implementation of new technologies may come from two different sources: a fall in the relative prices of machines q_t and a raise in the productivity of machines λ_t. Both cases may lead to occupations being fully automated when $W_{i,t} > \frac{q_t}{\lambda_t}$. This is the so-called displacement effect. However, in the labour intensive sector a decrease in the price of machines q_t and a raise in the productivity of machines λ_t increase the productivity of labour, as the two factors are complementary. Thus, despite the fall in the price of machines relative to the wage, labour demand increases (the so-called productivity effect). The productivity effect also translates into higher wages, the higher the union bargaining power is. Finally, when the price of the intermediate input produced by occupations fall sufficiently, then there is a further increase in labour demand (the so-called reinstatement effect).

As for differences across population groups in the impact of new technologies on employment and wages, they will depend on the different strength of complementarity of the new technologies with human labour. It is also conceivable that employment and wage effects are more positive among young workers since they are more likely to invest in the skills more complementary with new technologies, especially if they are highly educated. On the contrary, middle age workers are more likely to be employed in jobs with tasks more likely to be automatised, so that negative employment and wage effects would be more visible in occupations with more workers this age range. The rest of the paper empirically explores the relationship of new technologies, in particular AI and computer software, and employment shares and relative wages by occupations.

3 Data

A number of studies examine the relationship of new technologies and jobs for the United States. We focus on Europe and provides empirical evidence for 15 euro area countries (Austria, Belgium, Germany, Estonia, Spain, Finland, France, Greece, Ireland, Italy, Lithuania, Luxembourg, Latvia, Netherlands and Portugal), and the United Kingdom. This paper also departs from most of the literature, which tends to focus on the impact of one type of technology only,[3] by looking at two different technologies, namely AI-enabled technologies and software.

Our unit of analysis is a sector-occupation cell. Occupations are categorised based on the International Standard Classification of Occupations (ISCO) and we use a three-digit disaggregation level. Sectors are grouped into six main aggregates: agriculture, construction, financial services, services, manufacturing and public services. Our analysis covers the period between 2011 and 2019.

Technology data We adopt existing measures of exposure to AI and software. For AI, we use the **AI Occupational Impact (AIOI) scores** developed by Felten et al. (2019), which we will also refer to as AI *(Felten et al.)*. These scores link advances in specific applications of AI to the skill characteristics by occupation to measure how much AI could affect each occupation. These scores are based on 2019 O*NET data for descriptions of occupations, and the Electronic

[3] Two notable exceptions are Webb (2020) and Acemoglu et al. (2022).

Frontier Foundation AI Progress Measurement dataset,[4] which measures progress in various AI applications from 2010 to 2015. Amazon's Mechanical Turk (mTurk) links these AI applications to abilities required for each occupation. The final aggregated score is weighted by the prevalence and importance of abilities within each occupation. Due to its narrow range, we standardise the AIOI scores to take up values between 0 and 1 in our sample. A higher AIOI score corresponds to a greater potential effect of AI on the occupation from 2010 to 2015.

We also use scores of occupations' **exposure to AI and software** from Webb (2020). These measures of exposure to technology are constructed by quantifying the textual overlap (verb-noun pairs) of patents (taken from Google Patents Public Data) to job descriptions from O*NET. Exposure to software differs from exposure to AI in that every action it performs has been specified in advance by a human (e.g. store data, generate image). By contrast, exposure to AI measures how much an occupation's tasks are amenable to be aligned with machine learning algorithms (e.g. classify data, recognise image).

Our two AI measures (Felten et al. and Webb) slightly differ in the way they capture the applicability of AI to a task. While both measures focus on identifying tasks that fall within existing capabilities (either by relying on the reports from the AI Progress Measurement project or based on the text of patents), differences in the construction of measures exist. The AI measure by Felten et al. emphasises workers' abilities required due to occupations' exposure to AI advancements, whereas the measure by Webb highlights the availability of machine learning algorithms that are aligned with occupations' tasks.

Labour market data For harmonised employment information we use the EU Labour Force Survey (EU-LFS), annual microdata, for the period 2011-2019. This survey provides detailed cross-country labour force composition information. We are particularly interested in employment shares and their variation over time by occupation,[5] which are available at the either two- or three-digits ISCO level. We consider six sectors: agriculture, construction, financial services, services, manufacturing and public services.[6] For wages, we use the monthly pay from main job, which the EU-LFS provides in deciles. We measure wages by within country centiles of employment-weighted average wages for each sector-occupation cell in 2011, constructed using

[4]This is a dataset that tracks reported progress on metrics of AI performance across separate AI applications, such as image recognition, speech recognition, translation, or abstract strategy games.

[5]We exclude armed forces occupations from our sample.

[6]Original data are classified according to the Statistical Classification of Economic Activities in the European Community (NACE). Sector aggregates (corresponding NACE Rev. 2 classification): Manufacturing (C), Services (G-J,L-N,P-S), Public sector (O-Q) and Financial services (K)

individual data on wage centiles. Education is grouped into low (lower secondary education or lower), medium (up to post-secondary, non-tertiary education), and high (tertiary education).[7]

Our database In order to empirically assess the potential impact of technology on the labour market, we have to merge the labour market data with measures of exposure to technology. We merge the information from our different data sources and assure matches on several dimensions (provided these dimensions are available in the individual data sets): country, year, occupations (three-digits ISCO wherever possible) and sector. Scores taken directly from the literature (i.e. AI and software exposure scores), are generally provided for occupations classified in the Standard Occupational Classification (SOC) system, which is a US federal statistical standard. Since our micro-data on employment (specifically, the EU-LFS) uses the ISCO classification system, we have to merge occupation classifications. To do so correctly, we use crosswalks and correspondence tables from Hardy et al. (2018), U.S. Bureau of Labor Statistics (2012), ILO (2010), and also manually match remaining occupations. We perform these crosswalks at the four-digits ISCO level, and aggregate scores from the literature whenever the SOC's granularity exceeds the one of ISCO, and also whenever we calculate values for the more aggregated three digit occupation groups. For example, the AIOI scores that we take from Felten et al. (2019) are calculated at the eight-digit SOC level. We match SOC to ISCO occupations for both ISCO revisions, 2008 and 1988. Whenever ISCO occupations match to several SOC occupations, we take the average AIOI score across ISCO occupations. While this gives us the scores for 4-digit ISCO occupations, we drop the last digit to obtain three-digit occupations instead and take the mean for the occupations with the same three digits. Importantly, our measures of technology exposure have been constructed for the US economy and thus we use them under the implicit assumption that tasks are equally exposed to technology in the EU countries than in the US, where tasks exposures were originally measured. This assumption does not look unreasonable and it has the advantage that in our sample the occupation exposure measures are not that endogenous to employment and wage changes. The time dimension and frequency of our individual data sources vary. For the purpose of our analysis, we use annual values of the labour force composition (from the EU-LFS). The occupation-based scores and indicators are generally invariant over time. Specifically, the AIOI are based on AI technology progress between 2010 and 2015 on occupation descriptions from 2019. Note that our technology variables vary across

[7]This refers to the highest educational attainment using the International Standard Classification of Education (ISCED).

countries because we transform the raw scores (at 3-digit ISCO) into percentiles weighted by the occupation-sector cells employment.[8]

In 2011, there was a break in the ISCO classification (from ISCO88 to ISCO08). This reclassification of occupations renders it impossible to make meaningful comparisons of occupations before and after 2010, unless occupational information is given at the most granular level. Unfortunately, this is not the case for our data, which is why our sample starts in 2011. We do not consider this to be an issue for the analysis of the impact of AI-enabled technologies on the labour market, as these technologies start having important breakthroughs mostly after 2010.

4 Descriptive Evidence

This section provides some descriptive statistics for the technology measures of AI and software for the European countries in our sample.

Table 1 provides simple summary statistics of our three technology measures as defined in the previous section: AI by Webb, AI by Felten et al., and software by Webb. The two measures by Webb are available for 122 distinct occupations in our data set. They have very similar means (0.42 for the AI measure and 0.46 for the software measure) and standard deviations (0.17 and 0.18 respectively). The standardised AI measure by Felten et al. is available for 104 distinct occupations in our data set and averages by construction at 0.5 with a standard deviation of 0.26.

Table 1: Summary statistics of technology measures

Technology measure	N	Mean	SD	Min	Max
AI (Webb)	122	0.42	0.17	0.03	0.9
AI (Felten et al.)	104	0.5	0.26	0	1
Software (Webb)	122	0.46	0.18	0.12	1.05

Notes: Summary statistics of technology measures across all available occupations (unweighted). N corresponds to the number of distinct occupations in our data set, for which the technology measure provides a value.

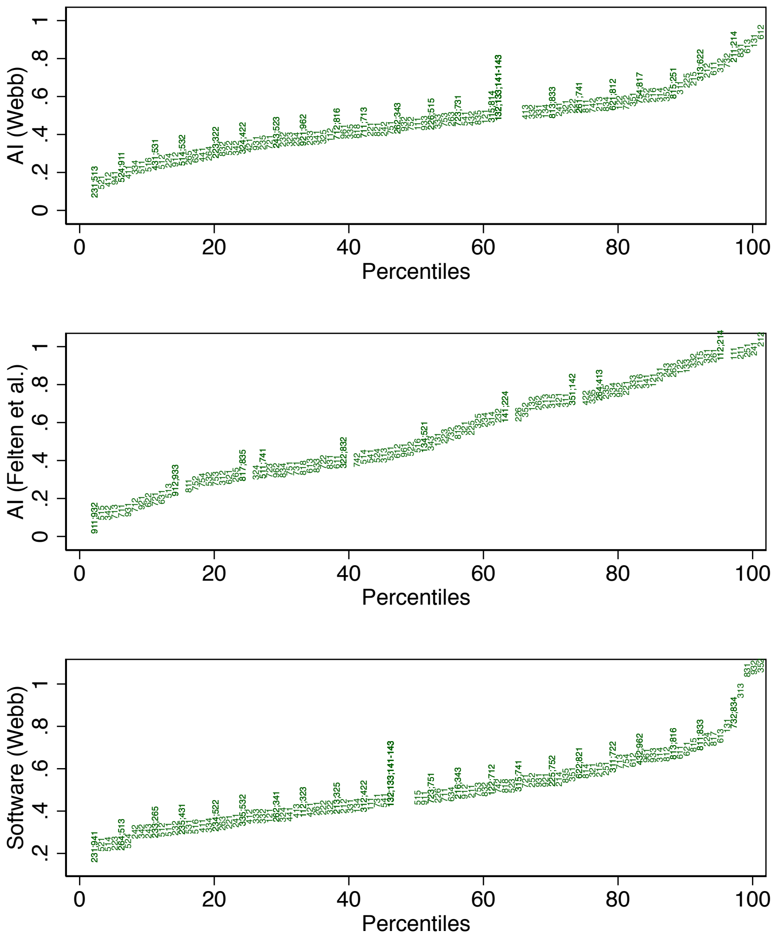
To get a better idea of how individual occupations vary and rank along our technology measures, Figure 1 shows the detailed distribution of our technology measures by occupation. Two main facts stand out. First, the potential impact of new technologies measured by these indi-

[8] Webb (2020) uses employment-weighted percentiles and Acemoglu et al. (2022) use the standardised mean of occupation AI exposure weighted by the number of vacancies posted.

cators is quite heterogeneous across occupations. Table 2 zooms in on the top and bottom five occupations based on each of the different technology measures, and provides their respective technology scores. Strikingly, between our two AI measures, there is barely any overlap of these occupations (only one occupation ranks in the top five for both measures), and only three out of ten occupations overlap between Webb's AI and software measures. Secondly, despite the lack of overlapping of occupations at the very top and at the very bottom of the distributions across technology measures, the overall rankings of occupations by the two measures of the potential impact of AI are quite similar. Spearman's rank correlations show that the different technology measures do correlate with each other and the null hypothesis that the ranking of occupations by any two measures is independent can be rejected ($r_s = 0.64$). However, the Webb's software measure and Felten et al.'s AI measure are negatively correlated ($r_s = -0.29$), which is a clear signal that new AI technologies are not only about the application of software, and warns that AI and digitalisation may impact jobs differently.

Appendix A shows further descriptive evidence, displaying changes in employment shares and relative wages between 2011 and 2019, and highlighting heterogeneity in technology measures themselves, but also heterogeneity in these measures by country, and by worker characteristics (i.e. education and age).

Figure 1: Distribution of occupations by technology measures and corresponding Spearman's rank correlations



	AI (Webb)	AI (Felten et al.)	Software (Webb)
AI (Webb)	1.00		
AI (Felten et al.)	0.20 (0.04)	1.00	
Software (Webb)	0.64 (0.00)	-0.29 (0.00)	1.00

Notes: 3-digit ISCO 2008 occupations ranked by percentiles (x-axis) of their location in the distributions based on the three technology measures. Y-axis indicates actual values of technology scores. For better visibility, average scores are displayed in the top three panels of the figure whenever multiple occupations rank at the same percentile. The bottom part of the figure shows Spearman's rank correlations, and p-values in brackets below a test of the H0 that variables are independent.

Table 2: Technology scores of top and bottom five occupations by technology measures

Technology measure	Top			Bottom		
	Rank	Occupation	Score	Rank	Occupation	Score
AI (Webb)	1	Animal producers (612)	0.9	1	University and higher education teachers (231)	0.03
	2	Production managers in agriculture, forestry and fisheries (131)	0.86	2	Waiters and bartenders (513)	0.1
	3	Mixed crop and animal producers (613)	0.83	3	Street and market salespersons (521)	0.11
	4	Locomotive engine drivers and related workers (831)	0.8	4	Secretaries (general) (412)	0.12
	5	Physical and earth science professionals (211)	0.8	5	Food preparation assistants (941)	0.13
	Top 5 Average		0.84	Bottom 5 Average		0.1
AI (Felten et al.)	1	Mathematicians, actuaries and statisticians (212)	1	1	Domestic, hotel and office cleaners and helpers (911)	0
	2	Finance professionals (241)	0.95	2	Manufacturing labourers (932)	0.03
	3	Software and applications developers and analysts (251)	0.94	3	Building and housekeeping supervisors (515)	0.09
	4	Physical and earth science professionals (211)	0.93	4	Sports and fitness workers (342)	0.09
	5	Legislators and senior officials (111)	0.93	5	Painters, building structure cleaners and related trades workers (713)	0.09
	Top 5 Average		0.95	Bottom 5 Average		0.06
Software (Webb)	1	Telecommunications and broadcasting technicians (352)	1.05	1	University and higher education teachers (231)	0.12
	2	Manufacturing labourers (932)	1.04	2	Food preparation assistants (941)	0.2
	3	Locomotive engine drivers and related workers (831)	1.03	3	Street and market salespersons (521)	0.21
	4	Process control technicians (313)	0.93	4	Hairdressers, beauticians and related workers (514)	0.21
	5	Mobile plant operators (834)	0.81	5	Traditional and complementary medicine professionals (223)	0.21
	Top 5 Average		0.97	Bottom 5 Average		0.19

Notes: 3-digit top and bottom five occupations by technology measures (ISCO 2008 classification in brackets), including actual technology scores.

5 Empirical Analysis

We now explore the relationship between occupations's exposure to AI and software and changes in employment shares and relative wages. We report these relationships by means of the coefficients β_c in the following regression:

$$y_{so,c} = \alpha_c + \alpha_s + \beta_c X_{so,c} + \epsilon^S_{so,c} \tag{8}$$

where the dependent variable $y_{so,c}$ is either the change in the employment share of sector-occupation so in country c during the 2011-2019 period, or the change in the wage distribution position of sector-occupation so in country c during the same period.

The change in the employment share is measured as a percentage change relative to the midpoint of a cell's share of overall employment between 2011 and 2019, winsorised at the top and bottom 1%.[9] The change in the wage distribution is captured by the change in the within-country centile of the employment-weighted average wage for each sector-occupation cell from 2011 to 2019.

$X_{so,c}$ are the measures of potential exposure of the sector-occupation so units to AI and to software as described in Section 3. As already discussed, these measures capture to what degree tasks, and thus occupations, could be performed by AI and by software. Therefore, we understand them as proxies to potential AI- and software-enabled automation, such that the estimated coefficients measure the potential impact of AI- (software-) enabled automation on changes in the employment share or in relative wages. Hence, a negative (positive) β_c indicates that potentially more automatised sector-occupations had declining (increasing) employment shares or relative wages. Observations are weighted by cells' average employment, standard errors are sector-clustered.

Depending on the sign of the β_c coefficients in the employment and wage equations, the relationship between technologies and jobs can be understood as being one of complementarity, displacement, or both. When the β_c coefficient is positive in both equations, i.e automation proxied by exposure to new technologies is associated with increases in both employment shares and relative wages, an increase in productivity is the dominant effect of technology and we label the technology employment relationship as one of complementarity. In contrast, a negative sign in both β_c coefficient (more technological exposure associated with decreases in both employment

[9] This is a second-order approximation of the log change for growth rates near zero. Also known as arc percentage change, and used in related literature, see for example Davis et al. (1996) and Webb (2020).

shares and relative wages) is interpreted as automation displacing employment. There could also be cases, in which one of the two coefficients is positive and the other negative, or some of them remain unchanged, this pattern is consistent with the so called a reinstatement effect, where some tasks or jobs are destroyed by automation, but new ones are created within the same occupation-sector cell.

The model presented previously in Section 2 illustrates how the relative sizes of the productivity, displacement and reinstatement effects associated with technological changes can be rationalised. The statistical associations reported in this section just provide a first approximation to the potential effects of new technologies on jobs across countries, as measured by alternative indexes of potential exposure to AI and changes in employment shares and relative wages of occupations.

5.1 Pooled Results

We start discussing results for the pooled sample of countries.[10]

Artificial intelligence We find a positive association between AI-enabled automation and changes in employment shares in the pooled sample. This is the case regardless of the indicator of exposure to AI used to proxy AI-enabled automation, as implied by the positive and significant coefficients on the first column in panel (a) and (b) in Table 3.[11]

According to the AI exposure indicator by Webb, on average in Europe, moving from centile 25 to centile 50 along the distribution of exposure to AI is associated with an increase of sector-occupation employment share of 2.6%, while using the measure provided by Felten et al. the estimated increase of sector-occupation employment share is 4.3%. The finding of a positive association supports the view that displacement effects of AI-enabled automation are small.

When estimating equation (8) for changes on relative wages we find that more AI exposure does not seem to be associated to changes in relative wages (see Table 4, first column in panel (a) and (b)). As discussed above, this coefficient depends both on the technology and the labour market institutions that condition wage-determination. Hence, it is plausibly related

[10]These include Austria (AT), Belgium (BE), Germany (DE), Estonia (EE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Lithuania (LT), Luxembourg (LU), Latvia (LV), Netherlands (NL), Portugal (PT), and United Kingdom (UK).

[11]This table and the results discussed in this section refer to the simplest specification as in column 1 of Table B1 in Appendix B. Columns 2-5 of Table B1 show results for various specifications, interacting sector and country dummies and including as additional regressors measures of exposure to Robots and Software.

to the rigidity of relative wages in Europe, where collective bargaining is prevalent in wage determination.

Table 3: Change in employment vs. exposure to technology. Pooled sample. 2011-2019

	All	Younger	Core	Older	LowEduc	MedEduc	HighEduc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(a) AI, Webb	0.104***	0.212***	0.106**	0.015	-0.008	-0.028	0.125**
	(0.035)	(0.050)	(0.047)	(0.038)	(0.056)	(0.053)	(0.055)
Obs.	6767	2160	1653	2954	2145	1979	2641
(b) AI, Felten et al.	0.174***	0.219***	0.132**	0.144***	-0.088	-0.068	0.266***
	(0.044)	(0.073)	(0.050)	(0.040)	(0.092)	(0.097)	(0.083)
Obs.	5766	1828	1369	2569	1809	1632	2323
(c) Software	-0.025	0.107***	-0.083*	-0.117**	0.004	-0.032	0.044
	(0.020)	(0.032)	(0.046)	(0.050)	(0.040)	(0.049)	(0.036)
Obs.	6839	2160	1653	2954	2145	1979	2641

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in employment share from 2011 to 2019 winsorised at the top and bottom 1 percent. Sample: 16 European countries, 2011 to 2019. The sub-sample in column (2) (3) and (4) consist of sector-occupation cells whose workers average age was in the lower, middle and upper tercile respectively of their country's workers age distribution in 2011. The sub-samples in column (5), (6) and (7) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.

Technology-enabled automation might also induce changes in the relative shares of employment along the skill distribution and thus impact within-occupation earnings inequality. The literature on job polarisation shows that medium skilled workers in routine intensive jobs were replaced by computerisation, in line with the so-called Routinisation theory. In contrast, it is often argued that AI-enabled automation is more likely to either complement or displace jobs in occupations that employ high skilled labour, in line with the SBTC theory.[12] In what follows we examine whether the impact of AI-enabled automation is concentrated on certain groups of workers, varying by either educational attainment (skills) or age.

We split sector-occupation cells within each country by age and skills terciles in 2011, the initial year of our sample, so that the first age tercile includes those observations (sector-occupation cells) whose average age was in the lower tercile of the country's age distribution in our sample in 2011, we name this first tercile as younger, the second as core and the third as older. Similarly, for skills, each tercile consists of these sector-occupation cells whose average educational attainment is in the low, medium and high tercile respectively of the education distribution within each country.

Plots (a) and (b) in Figure 2 display the estimated coefficients of the association between

[12] For a discussion on these two theories see Section 1 and Goos and Manning (2007).

Table 4: Wage changes and technology exposure. Pooled sample 2011-2019

	All	Younger	Core	Older	LowEduc	MedEduc	HighEduc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(a) AI Webb	0.001	0.012	0.007	-0.009	-0.014	0.009	0.034**
	(0.007)	(0.011)	(0.016)	(0.013)	(0.010)	(0.013)	(0.012)
Obs.	5729	1772	1534	2423	1834	1648	2246
(b) AI, Felten et al.	-0.013*	0.004	-0.022	-0.021	-0.051	0.027	0.008
	(0.007)	(0.012)	(0.018)	(0.013)	(0.033)	(0.018)	(0.031)
Obs.	4872	1506	1263	2103	1550	1343	1978
(c) Software	0.007	0.018	0.015	-0.005	-0.010	-0.014	0.026**
	(0.008)	(0.011)	(0.015)	(0.017)	(0.008)	(0.014)	(0.011)
Obs.	5729	1772	1534	2423	1834	1648	2246

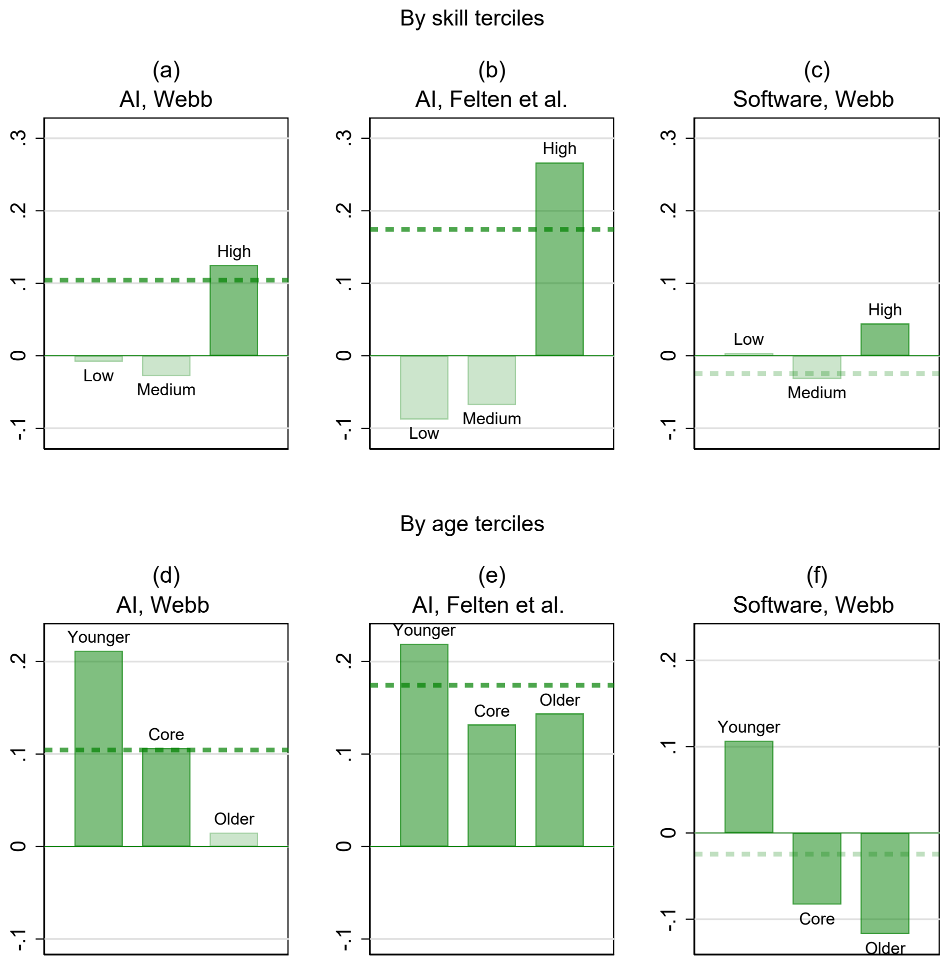
Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in relative wages from 2011 to 2019 winsorised at the top and bottom 1 percent.For Austria, Spain and Lithuania 2018 wages values were taken instead of 2019. For Finland 2017 wages were taken instead of 2019. For the UK 2013 wages were taken instead of 2011. These changes were implemented due to limited availability of data for the reference years. The sub-sample in column (2) (3) and (4) consist of sector-occupation cells whose workers age was in the lower/middle and upper tercile respectively of the country's workers age distribution in 2011. The sub-sample in column (5), (6) and (7) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.

changes in employment and AI-enabled automation for the terciles of occupations that employ low, medium and high skilled workers. The aggregate coefficient for all the skills is displayed by a red horizontal line, while the height of the green bars display the coefficient estimated for each one of the skill terciles. Significant coefficients are plotted in dark shaded colour (see also Table 3 columns 5 to 7).

While there are no significant changes in employment shares associated to AI for the low and medium skill terciles, for the high skilled there is a positive and significant association: moving 25 centiles up along the distribution of exposure to AI is estimated to be associated with an increase of sector-occupation employment share of about 3.1% using Webb's AI exposure indicator, and of 6.6% using the measure by Felten et al. These estimates are showing that the positive relationship between AI-enabled automation and employment growth that we uncovered for the pool of countries is driven by jobs that employ high skilled workers.

Plots (d) and (e) in Figure 2, and columns 2 to 4 in Table 3, report the estimates by age groups, according to which AI-enabled automation appears to be more favourable for those occupations that employ relatively younger workers. Regardless of the AI indicator used, the magnitude of the coefficient estimated for the younger group doubles that of the rest of the groups. AI-enabled automation in Europe is thus associated with employment increases, and

Figure 2: Exposure to technology and changes in employment share, by skill and age



Notes: Regression coefficients measuring the effect of exposure to technology on changes in employment share, as in Table 3. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells average labour supply. Sector and country dummies included. Sample: 16 European countries, 2011 to 2019. The coefficient for the whole sample is displayed by the horizontal dotted line. The bars display the coefficient estimated for the subsample of cells whose average educational attainment is in the lower, middle and upper tercile respectively of the education distribution (first row) and of cells whose workers average age is in the lower, middle and upper tercile respectively of workers age distribution (second row). Coefficients that are statistically significant at least at the 10% level are plotted in dark shaded colour.

this is mostly for occupations with relatively higher skill and younger workers.

Software In contrast, the estimated relationship between software-enabled automation and changes in employment shares is not significantly different from zero in the aggregate. For the medium skill tercile the relation is negative, which would be in line with job polarisation. However, this result is not statistically different from zero (see plot (c) in Figure 2 and panel (c) in table 3). Regarding age, panel (f) in Figure 2, there is a negative and significant relationship for occupations that employ relative older workers (core and older workers) and positive for those that employ younger workers. Thus, we do not identify for Europe a remarkable impact of software on employment shares for the period of analysis, 2011-2019, and of software replacing routine medium skill jobs. One could think that this might be specific to the period of analysis 2011-2019. However, even if we find a negative association between software and changes in employment shares in the pooled sample for the period 2000-2010, we do not find evidence to support the Routinisation theory in that period, see table B6.

5.2 Results by Country

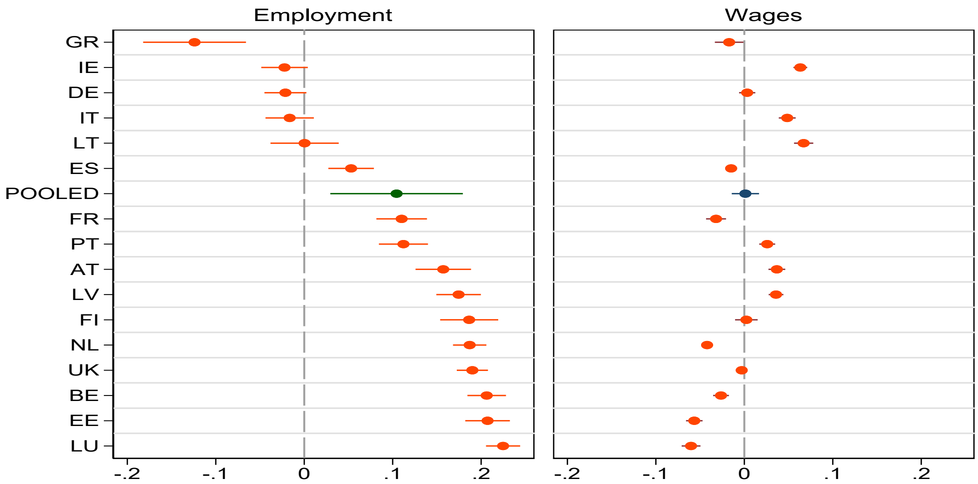
In this subsection we explore the impact of new technologies within countries. Our prior is that it will vary depending on each country's distribution of employment across sectors and occupations, which are differently exposed to the technologies.

Artificial intelligence We find that while there is heterogeneity in the magnitude of the estimates, the positive sign of the relationship between AI-enabled automation and employment shares also holds at the country level with only a few exceptions. The country estimates can be seen in Figures 3 and 4, which in the left panel display the estimate coefficients from the employment shares equations for each country in the sample β_c, together with the one for the pooled sample of countries (our aggregate) β, with their statistical significance bands ordered by magnitude. The corresponding β_c and β from the relative wages equation are shown in the right panel.[13] A positive association between exposure to AI and changes in employment shares is observed for most of the countries; there are a few exceptions showing no relation, and the only exception where the relationship is negative is Greece when looking at Webb's AI exposure measure, and to a lower extent Lithuania and Ireland with Felten's AI exposure measure. Figure 5 compares the estimates in a scatter plot using both measures of AI.

[13]For detailed regression results see tables in Appendix B.

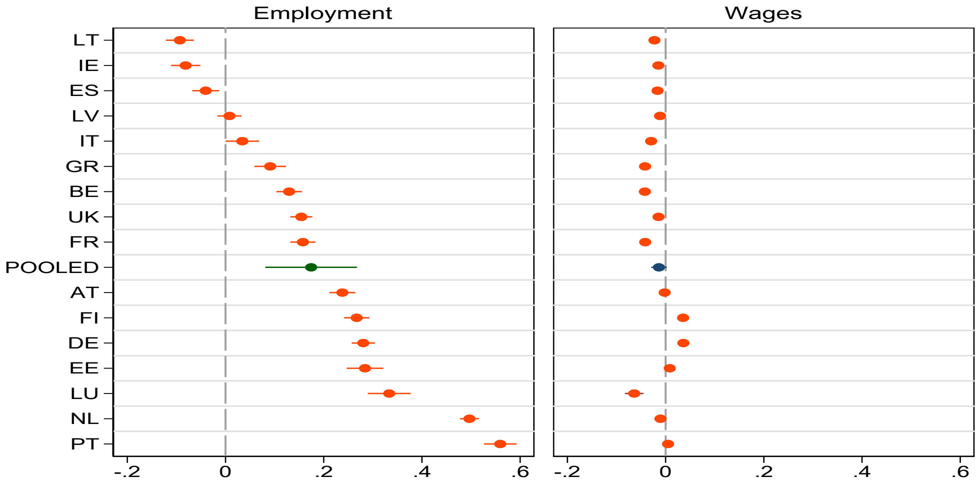
Regarding wages (see the right panel in Figures 3 and 4) in most of the countries (as in the pooled sample), the statistical association of changes in relative wages and AI measures is zero or negative. There are some remarkable exceptions for which more AI exposure is associated with increases of both the employment shares and relative wages of the sector-occupations, namely, Austria, Portugal and Latvia for the indicator by Webb and Germany and Finland for the one by Felten et al.

Figure 3: Exposure to AI, Webb, and changes in employment shares and wage percentiles, by countries



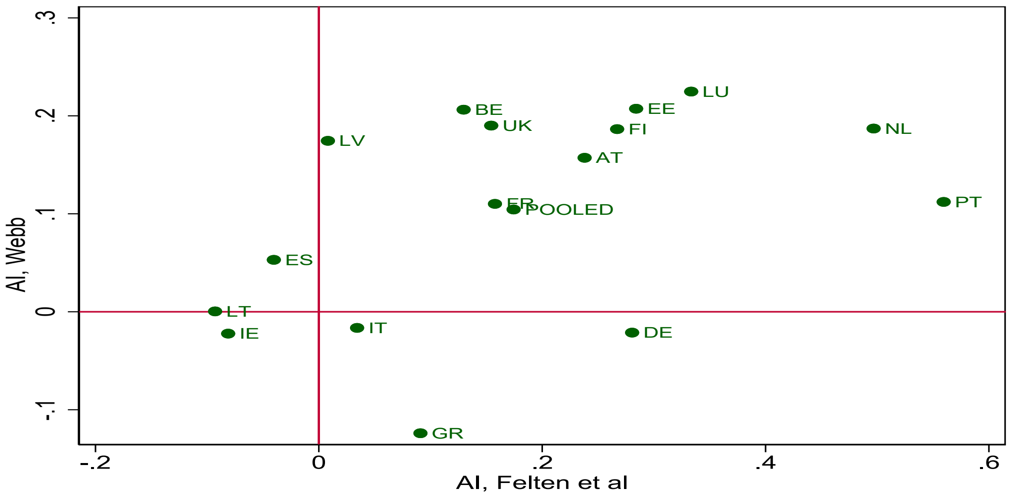
Notes: βc and β coefficients from employment shares and from relative wages regressions respectively in the same graph. See notes in tables B2 and B3.

Figure 4: Exposure to AI, Felten at al, and changes in employment shares and wage percentiles, by countries



Notes: βc and β coefficients from employment shares and from relative wages regressions respectively in the same graph. See notes in tables B4 and B5.

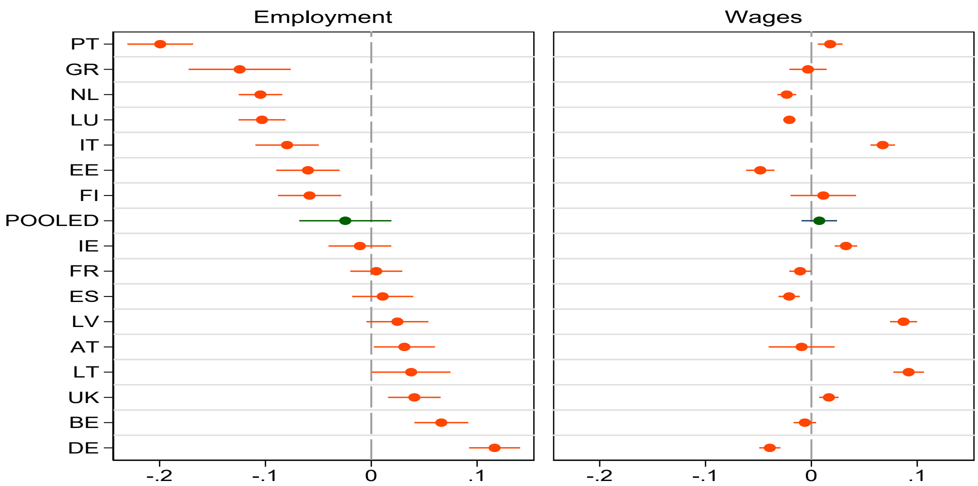
Figure 5: Exposure to AI, Webb and Felten et al., and changes in employment shares, by country



Notes: Scatter plot of regression coefficients measuring the effect of exposure to AI on changes in employment share. X-axis: regression coefficients using the AI proxy based on Felten et al. Y-axis: regression coefficients using the AI proxy based on Webb. For further details see notes to Figure 2.

Software Exposure to software is associated with declines in employment shares in quite a number of countries, namely Portugal, Greece, The Netherlands, Luxembourg, Italy, Estonia, and Finland, while is associated with increases in employment shares only in Germany, Belgium, and UK, as shown in Figure 6 and table B7 in the Appendix. The relationship is null from a statistical point of view for over a third of the countries in the sample and for the aggregate. However, in about a half of the counties of our sample the relationship employment - software appears to be negative for medium skilled workers, see Table B7, which is in line with the so called Routinisation or labour market polarisation.

Figure 6: Exposure to software, Webb, and changes in employment shares and wage percentile



Notes: βc and β coefficients from employment shares and from relative wages regressions respectively in the same graph. See notes in tables B7 and B8.

5.3 Interpreting Country Variation

The cross-country heterogeneity of the association between potential exposure to AI and employment shares may reflect different degrees of technology adoption and diffusion, and thus actual exposure of occupations to technology. Country-specific structural features affect adoption, diffusion and how the labour market reacts to the introduction of new technologies in the workplace. With a view to analysing the association of structural factors in explaining our country estimates we correlate the country estimates with indicators of technology adoption and structural features of the European countries in our sample.

We first use the Digital Economy and Society Index (DESI) of the European Commission as a measure of technology exposure. The DESI tracks progress in the EU member states in the area of digital technologies. According to this measure the top three countries of our sample are Finland, the Netherlands and Austria and the bottom three are Greece, Italy and Latvia. The rank correlations show that the positive impact of AI-enabled technologies on employment is higher in countries with higher DESI. The correlation for software exposure is negative and close to zero (Table 5). The correlation results are similar using the World Governance Indicators (WGI). This indicator measures a broad set of structural characteristics[14] that could potentially affect both adoption and diffusion and the reaction of the labour market to technological innovation. The results of both the DESI and WGI point to higher employment effects in countries with larger exposure to digital technologies, possibly the countries where diffusion of technology is likely taking place faster.

We also use the OECD's indicators of Product Market Regulation (PMR) and Employment Protection Legislation (EPL) to assess the degree of association between the level of competition and labour market rigidities with the employment estimates at the country level. Rigidities may either retard technological diffusion or smooth its impact on employment shares. Thus, the higher the indicator of product market regulation (lower competition) and the higher the indicator of employment protection (lower flexibility) are, the lower the impact of technology on employment is. In this case, the results for PMR and EPL give a similar message as that of the DESI and WGI.

Lastly, we analyse the correlation between our country results and measures of education attainment and quality of education outcomes. In particular we use the share of workers with tertiary education and the OECD's PISA scores. We observe a positive correlation between these measures and our country estimates on the effects of AI-enabled technologies on employment. One can read these results in two ways. First, AI-enabled technologies appear to complement high skilled jobs, at least at this early stage of development. Second, the actual adoption of frontier technologies depend on the capital endowment of a country, and thus the positive correlation we found may also capture the degree of diffusion. In the latter case our correlation results would point in the direction of a higher diffusion of AI-enabled technologies be associated with a higher positive impact of these technologies on employment.

[14]The indicator is a simple average of the following elements: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption.

Table 5: Correlations between country estimates and institutions

	AI (Webb)	AI (Felten et al.)	Software (Webb)
Digital Economy and Society Index	.40	0.42	-0.08
World Governance Indicators	0.51	0.31	-0.05
Employment Protection Legislation	-0.08	-0.17	-0.33
Product Market Regulations	-0.50	-0.30	-0.12
Pisa score	0.30	0.32	0.20
Share of tertiary education	0.31	0.24	-0.22

Notes: Spearman's rank correlations. DESI includes human capital, connectivity, integration of digital technology and digital public services. WGI includes voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption.

6 Conclusion

In this paper we explore the potential impact of AI- and software-enabled automation on European labour markets over the period 2011-2019.

We use occupational measures of AI exposure provided by Webb (2020) and Felten et al. (2019) as proxies to potential AI-enabled automation and find that AI-enabled automation in Europe is associated with employment increases. This positive relationship is mostly driven by occupations with relatively higher proportion of skilled workers, which is in line with the SBTC theory. The relationship between AI and wages turns out to be negative and hardly significant for the Felten et al.'s measure and statistically not significant for the Webb's measure.

Our results show heterogeneous patterns across countries. The positive impact of AI-enabled automation on employment holds across countries with only a few exceptions. However, the magnitude of the estimates largely varies across countries, possibly reflecting different economics structures, such as the pace of technology diffusion and education, but also to the level of product market regulation (competition) and employment protection laws.

The relationship between software exposure and employment changes is also heterogeneous across countries, but null for the aggregate. In addition, wages do not appear to be affected in a statistically significant manner from software exposure, which is somewhat at odds with the seminal work on the effect of digital technologies on wages (Krueger 1993 and Autor et al. 1998). Overall, we do not identify for Europe as a whole a remarkable impact of software on employment changes and our findings hardly support the hypothesis of software replacing routine medium skill jobs. However, for a number of individual countries in the sample the relationship employment - software appears to be negative for medium skilled workers, which is in line with the Routinisation theory.

Our results on the positive association between AI-enabled automation and employment should be taken with caution. These technologies are still in their early stages. While in the period of our analysis the association is positive, these results may not be extrapolated into the future, especially if the path followed by AI technologies focused on the automation of tasks and lead to the creation of few new tasks.

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Appendix A: Additional Descriptive Evidence

This appendix complements the descriptive evidence shown in Section 4.

How are technology requirements of occupations linked to workers and subsequently employment in general? Table A1 provides first insights on this by giving an overview of technology measures and workers, showing the average percentile of each technology measure by certain worker characteristics (i.e. education and age).[15] Generally, more highly educated workers are in occupations with higher AI technology scores, contrasting their relatively lower exposure to average software compared to lower educated workers. Table A2 then shows the employment shares in 2011 and 2019, and the respective change by worker demographics (i.e. education and age). Similarly, table A3 shows relative wages and their changes. Across the three skill groups, employment shares are fairly even around a third each, and slightly grew for the medium- and high-educated groups, while the low-educated group's employment share fell by 1.58 percentage points, which was the largest change in absolute values of all groups. Similarly, employment shares across age groups are evenly sized around a third. The employment share for the middle-aged group is distinctively the lowest (30.95 percent in 2011), and fell the most (by 0.34 percentage points). The largest increase was seen for the young (1.23 percentage points), while the old slightly decreased their employment share (by 0.08 percentage points). The average wage decile slightly increased for all skill and age groups, with the young and low-educated workers seeing the highest increases in their average wage decile (by 0.24 and 0.26, respectively), and the old and high-educated seeing the lowest increases (by 0.14 and 0.12, respectively). Figure A1 and figure A2 visualise these observations for employment shares and wage deciles respectively.

Figure A3 shows employment changes for occupations with low, medium or high technology scores. While there are differences across technology measures, regardless of the technology measure, employment shares generally increased slightly for high-scoring occupations. Strikingly, occupations scoring lowest for AI (Webb) have the highest employment share, contrasting AI (Felten et al.), where the group of occupation that score lowest has the smallest employment share. Considering wage deciles, the picture is more similar between the two AI measures: occupations scoring higher for any AI measure, are also linked to a higher wage decile. Only for the software measure the trend is reversed, meaning that higher software scores appear to be linked to lower wage deciles (see Figure A4).

Some of the changes in employment shares and wage deciles that are discussed here may be

[15] Note that education terciles are also referred to as skill terciles in this paper.

masking heterogeneity across countries that fails to become evident in the pooled sample. An overview of all the countries and their respective employment shares and wage deciles are shown in Figures A5 - A14).

Figure A15 emphasises the heterogeneity across technology measures and countries for changes in employment shares and wage deciles in the period 2011-2019. Employment shares have remained broadly the same in the top and bottom 40 occupations ranked by the potential impact of Webb's AI meaure. However, when using the Felten et al. measure of the potential impact of AI, employment shares have increased by more in the top 40 occupations, and decreased in the top bottom 40 occupations. In contrast, digitalisation seems to have increased them by more in the bottom 40 occupation ranked according to the software (Webb) measure.

As for relative wages, the potential impact of AI is different depending on the measure. According to AI by Webb, relative wages in top 40 occupations increased faster than in the bottom 40 occupations, whereas according to the AI measure by Felten et al., the reverse is true. Moreover, the digitalisation measure – software by Webb – does not show a clear pattern of changes in relative wages.

The aggregate descriptive patterns of changes in employment and relative wages by technology measures are not driven by specific groups of countries. Results are in fact very heterogeneous across countries too. As for employment shares, the largest cross country heterogeneity is observed with the AI (Webb) measure of technology. According to AI (Felten et al.) measure, employment shares in most countries increased in the top 40 occupations and decreased in the bottom 40 occupation. The opposite is observed for the software (Webb) measure. Comparing changes in employment and relative wages by technology measure, the correlation between changes in employment share and income deciles appears weak. A more detailed description is presented in Table A4 (Table A5). These two tables shows the top and bottom five occupations by each technology measure, the employment shares (wage deciles) in 2011 and 2019, and the respective change between these years. Across technology measures and both years, the employment share for the top five occupations (combined ranges between 0.62 and 0.9) is much smaller than the employment share for the bottom five occupations (combined ranges between 1 and 1.37). For occupations ranking high in Webb's AI and software scores, the employment share fell in total by 0.21 and by 0.02 percentage points, while the employment share for occupations high in Felten et al.'s AI measure increased by 0.15 percentage points. This contrasts what we observe for the bottom five occupations of each measure. Here, regardless of the technology measure, the employment share increased in total between 0.04 and 0.07 percentage points. Looking at wages in table A5, top occupations across all technologies are in higher deciles in both years (on average between the 5.7th and the 8.05th decile) than bottom occupations (on average between the 3.79th and the 4.85th decile). The change in average wage decile between 2011 and 2019 for the top five occupations was positive irrespective of the technology measure (increase between 0.24 and 0.35). For the bottom five occupations, we also see increases in the average unweighted income deciles ranging between 0.1 for occupations low on Felten et al.'s AI score, and 0.55 for occupations scoring low on software. The latter was largely driven by a sizeable wage increase for traditional and complementary medicine professionals. These somewhat mixed results confirm our believes that to draw any meaningful conclusions, controlling for observables is important, as well as implementing employment-weights in our empirical analyses.

Table A1: Percentile of technology measures by worker demographics

		Percentiles		
	Technology Measure	Low	Medium	High
Education	AI (Webb)	53.14	53.77	63.56
	AI (Felten et al.)	26.61	48.02	75.12
	Software (Webb)	70.66	54.53	47.46
Age	AI (Webb)	56.51	57.06	58.23
	AI (Felten et al.)	52.24	52.98	51.70
	Software (Webb)	55.75	56.71	57.84

Notes: The table reflects how exposed different education and age groups of workers are on average to our three technology measures. Education categories (low, medium, high) reflect terciles of a country's educational attainment distribution. Age categories (low, medium, high) reflect terciles of workers' age distribution in 2011. The average ranking is based on employment-weighted distributions for all technology measures.

Table A2: Employment shares and their changes by worker demographics

		Low	Medium	High
Education	Employment Share 2011	33.65	31.88	32.29
	Employment Share 2019	32.07	32.04	32.51
	Change	-1.58	0.16	0.22
Age	Employment Share 2011	34.65	30.95	32.21
	Employment Share 2019	35.88	30.61	32.13
	Change	1.23	-0.34	-0.08

Notes: Employment shares are shown as percentages, changes are percentage points. Classification of categories for age and education are benchmarked to 2011.

Table A3: Wage deciles and their changes by worker demographics

		Low	Medium	High
Education	Income Decile 2011	4.36	5.32	7.22
	Income Decile 2019	4.62	5.54	7.34
	Change	0.26	0.22	0.12
Age	Income Decile 2011	5.43	5.82	5.96
	Income Decile 2019	5.67	6.03	6.1
	Change	0.24	0.21	0.14

Notes: Wage shown as average unweighted annual deciles, changes are differences in average deciles. Classification of categories for age and education are benchmarked to 2011. For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values were taken due to limited availability of values for 2019.

Table A4: Employment shares and employment share changes of top and bottom five ISCO 2008 occupations by technology measures

Technology Measure	Rank	Top 5 occupations Occupation	Employment Share (%) (2011)	(2019)	(Change)	Rank	Bottom 5 occupations Occupation	Employment Share (%) (2011)	(2019)	(Change)
AI (Webb)										
	1	Animal producers (612)	0.22	0.2	-0.02	1	University and higher education teachers (231)	0.25	0.28	0.03
	2	Production managers in agriculture, forestry and fisheries (131)	0.04	0.05	0.01	2	Waiters and bartenders (513)	0.5	0.51	0.01
	3	Mixed crop and animal producers (613)	0.49	0.32	-0.17	3	Street and market salespersons (521)	0.13	0.11	-0.02
	4	Locomotive engine drivers and related workers (831)	0.09	0.07	-0.02	4	Secretaries (general) (412)	0.21	0.21	0
	5	Physical and earth science professionals (211)	0.06	0.05	-0.01	5	Food preparation assistants (941)	0.22	0.26	0.04
	Top 5 Combined		0.9	0.69	-0.21	Bottom 5 Combined		1.31	1.37	0.06
AI (Felten et al.)										
	1	Mathematicians, actuaries and statisticians (212)	0.02	0.02	0	1	Domestic, hotel and office cleaners and helpers (911)	0.54	0.56	0.02
	2	Finance professionals (241)	0.31	0.34	0.03	2	Manufacturing labourers (932)	0.22	0.22	0
	3	Software and applications developers and analysts (251)	0.23	0.38	0.15	3	Building and housekeeping supervisors (515)	0.15	0.15	0
	4	Physical and earth science professionals (211)	0.06	0.05	-0.01	4	Sports and fitness workers (342)	0.14	0.17	0.03
	5	Legislators and senior officials (111)	0.08	0.06	-0.02	5	Painters, building structure cleaners and related trades workers (713)	0.16	0.15	-0.01
	Top 5 Combined		0.7	0.85	0.15	Bottom 5 Combined		1.21	1.25	0.04
Software (Webb)										
	1	Telecommunications and broadcasting technicians (352)	0.07	0.06	-0.01	1	University and higher education teachers (231)	0.25	0.28	0.03
	2	Manufacturing labourers (932)	0.22	0.22	0	2	Food preparation assistants (941)	0.22	0.26	0.04
	3	Locomotive engine drivers and related workers (831)	0.09	0.07	-0.02	3	Street and market salespersons (521)	0.13	0.11	-0.02
	4	Process control technicians (313)	0.06	0.07	0.01	4	Hairdressers, beauticians and related workers (514)	0.38	0.4	0.02
	5	Mobile plant operators (834)	0.2	0.2	0	5	Traditional and complementary medicine professionals (223)	0.02	0.02	0
	Top 5 Combined		0.64	0.62	-0.02	Bottom 5 Combined		1	1.07	0.07

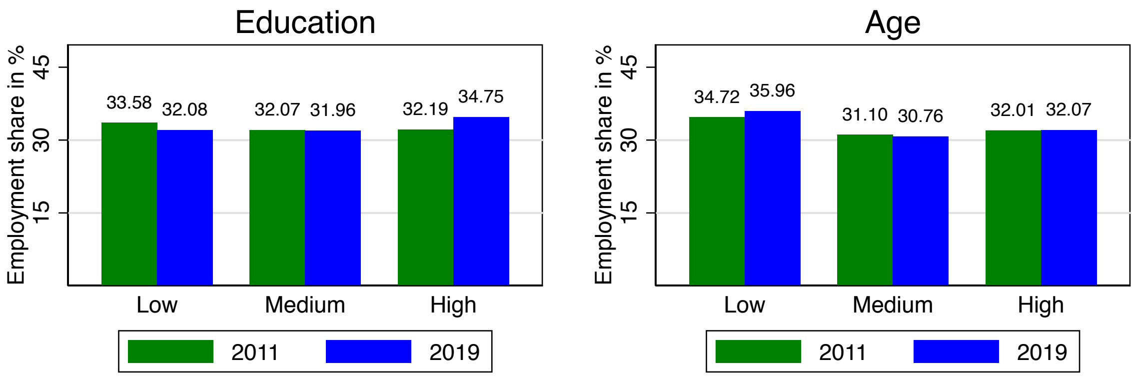
Notes: 3-digit top and bottom five occupations by technology measures (ISCO 2008 classification in brackets). Employment shares are displayed as percentages, changes in employment shares are given as percentage point differences.

Table A5: Wage deciles and wage decile changes of top and bottom five ISCO 2008 occupations by technology measures

Technology Measure	Top 5 occupations		Income Decile			Bottom 5 occupations		Income Decile		
	Rank	Occupation	(2011)	(2019)	(Change)	Rank	Occupation	(2011)	(2019)	(Change)
AI (Webb)										
	1	Animal producers (612)	3.59	3.86	0.27	1	University and higher education teachers (231)	7.63	7.78	0.15
	2	Production managers in agriculture, forestry and fisheries (131)	6.85	7.22	0.37	2	Waiters and bartenders (513)	3.34	3.23	-0.11
	3	Mixed crop and animal producers (613)	3.14	3.62	0.48	3	Street and market salespersons (521)	2.82	3.77	0.95
	4	Locomotive engine drivers and related workers (831)	7.3	7.56	0.26	4	Secretaries (general) (412)	4.78	4.83	0.05
	5	Physical and earth science professionals (211)	7.64	7.97	0.33	5	Food preparation assistants (941)	2.65	2.95	0.3
	Top 5 Average		5.7	6.05	0.35	Bottom 5 Average		4.24	4.51	0.27
AI (Felten et al.)										
	1	Mathematicians, actuaries and statisticians (212)	7.82	8.36	0.54	1	Domestic, hotel and office cleaners and helpers (911)	2.31	2.48	0.17
	2	Finance professionals (241)	7.49	7.63	0.14	2	Manufacturing labourers (932)	3.41	3.42	0.01
	3	Software and applications developers and analysts (251)	7.97	8.15	0.18	3	Building and housekeeping supervisors (515)	4.54	4.65	0.11
	4	Physical and earth science professionals (211)	7.64	7.97	0.33	4	Sports and fitness workers (342)	3.96	3.98	0.02
	5	Legislators and senior officials (111)	8.04	8.12	0.08	5	Painters, building structure cleaners and related trades workers (713)	4.75	4.93	0.18
	Top 5 Average		7.79	8.05	0.26	Bottom 5 Average		3.79	3.89	0.1
Software (Webb)										
	1	Telecommunications and broadcasting technicians (352)	6.45	6.73	0.28	1	University and higher education teachers (231)	7.63	7.78	0.15
	2	Manufacturing labourers (932)	3.41	3.42	0.01	2	Food preparation assistants (941)	2.65	2.95	0.3
	3	Locomotive engine drivers and related workers (831)	7.3	7.56	0.26	3	Street and market salespersons (521)	2.82	3.77	0.95
	4	Process control technicians (313)	6.61	6.95	0.34	4	Hairdressers, beauticians and related workers (514)	2.87	2.95	0.08
	5	Mobile plant operators (834)	5.45	5.74	0.29	5	Traditional and complementary medicine professionals (223)	5.53	6.81	1.28
	Top 5 Average		5.84	6.08	0.24	Bottom 5 Average		4.3	4.85	0.55

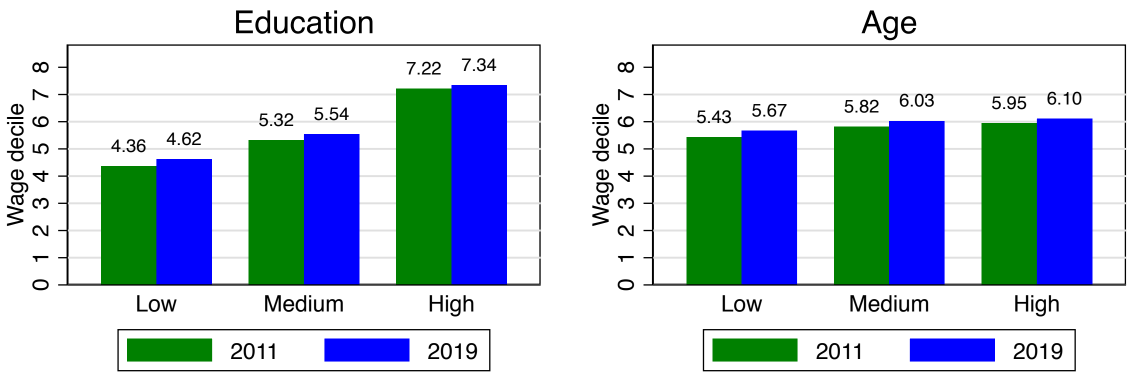
Notes: 3-digit top and bottom five occupations by technology measures (ISCO 2008 classification in brackets). Wage shown as average unweighted annual deciles, changes are differences in average deciles. For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values were taken due to limited availability of values for 2019.

Figure A1: Employment shares by worker demographics



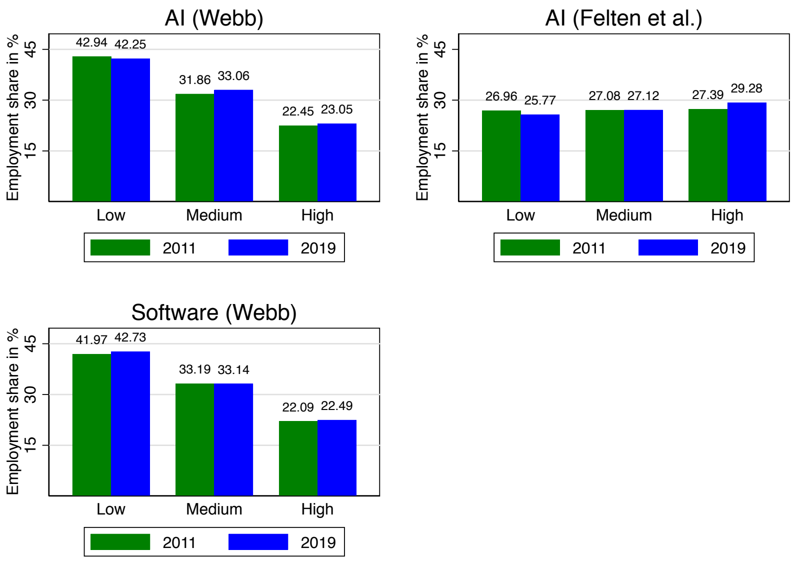
Notes: Y-axis indicates average annual employment shares. Education categories (low, medium, high) reflect terciles of a country's educational attainment distribution. Age categories (low, medium, high) reflect terciles of workers' age distribution in 2011.

Figure A2: Wage deciles by worker demographics



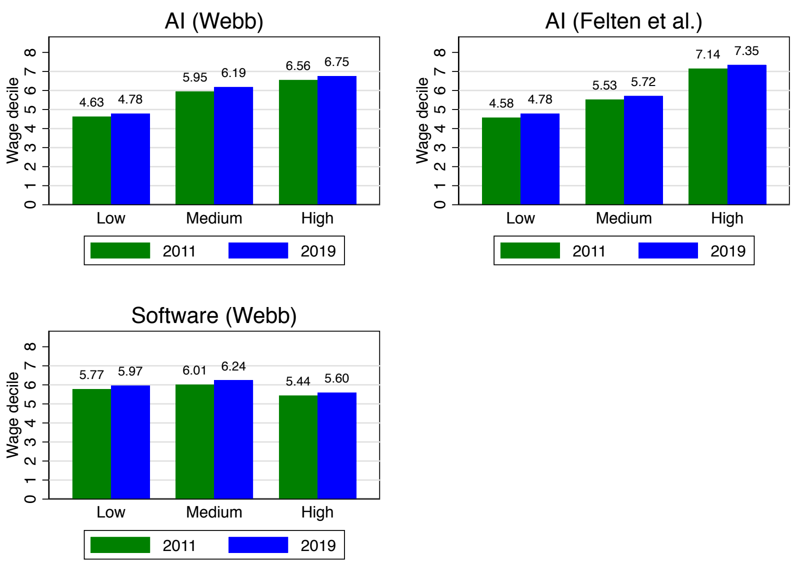
Notes: For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values were taken due to limited availability of values for 2019. Y-axis indicates average annual wage decile. Education categories (low, medium, high) reflect terciles of a country's educational attainment distribution. Age categories (low, medium, high) reflect terciles of workers' age distribution in 2011.

Figure A3: Employment shares by technology measures



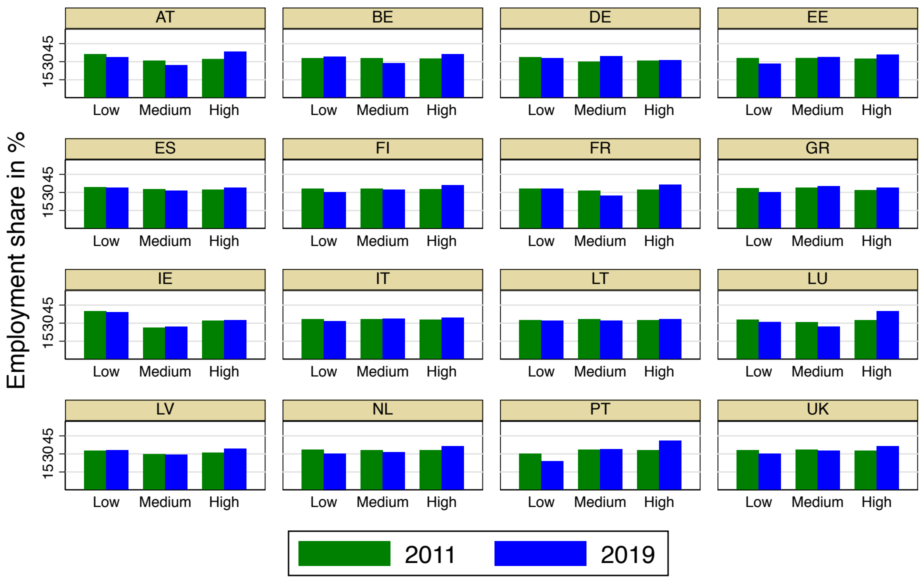
Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

Figure A4: Wage deciles by technology measures



Notes: For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values were taken due to limited availability of values for 2019. Y-axis indicates average annual wage decile. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

Figure A5: Employment shares by education across countries



Notes: Y-axis indicates average annual employment shares. Education categories (low, medium, high) reflect terciles of a country's educational attainment distribution.

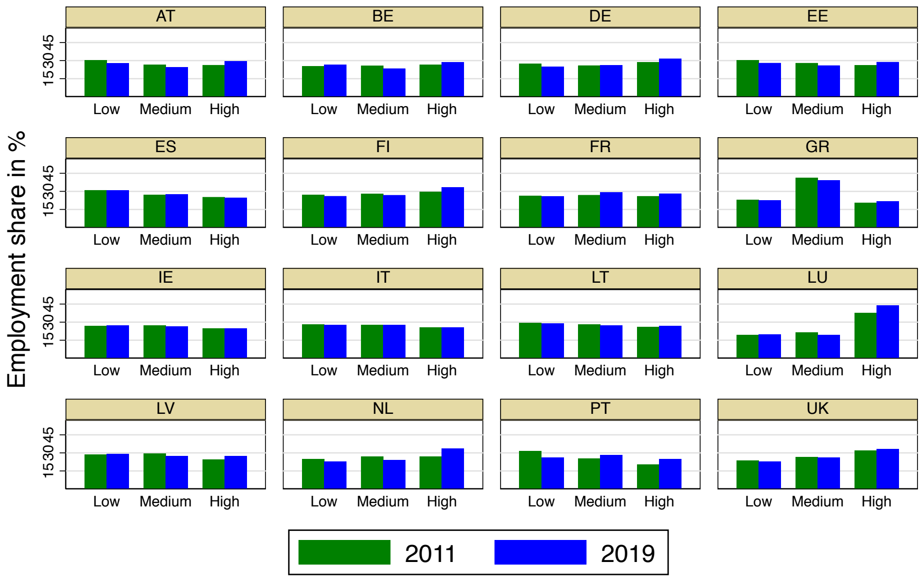
Figure A6: Employment shares by age across countries

Notes: Y-axis indicates average annual employment shares. Age categories (low, medium, high) reflect terciles of workers' age distribution in 2011.

Figure A7: Employment shares by AI (Webb) across countries

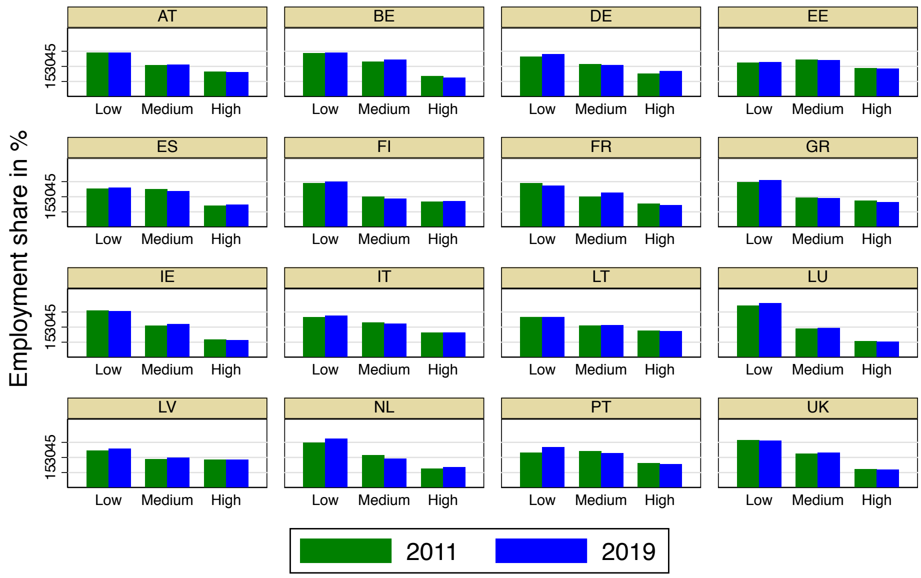
Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

Figure A8: Employment shares by AI (Felten et al.) across countries



Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

Figure A9: Employment shares by software across countries



Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

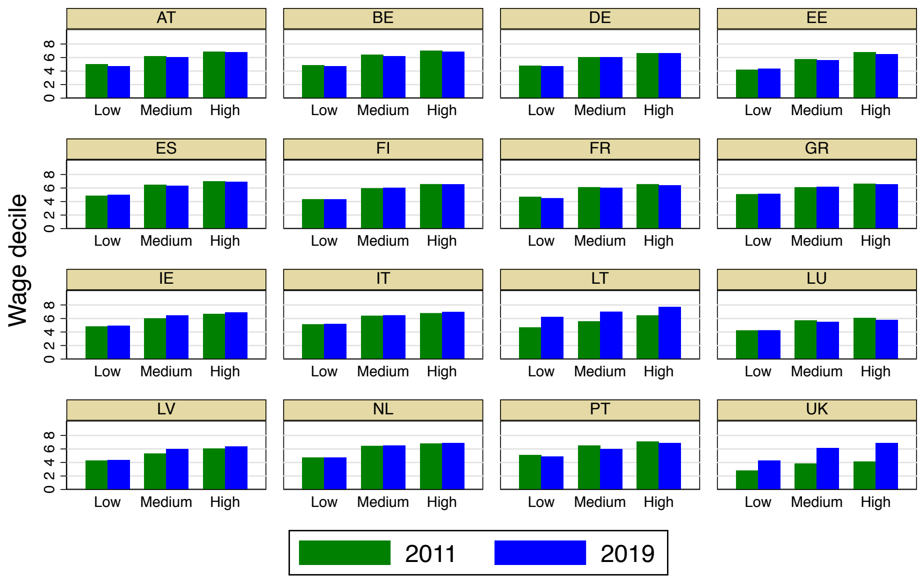
Figure A10: Wage deciles by education across countries

Notes: For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values were taken due to limited availability of values for 2019. Y-axis indicates average annual unweighted wage decile. Education categories (low, medium, high) reflect terciles of a country's educational attainment distribution.

Figure A11: Wage deciles by age across countries

Notes: Values for the UK are excluded for data limitation reasons. 2018 wage values were taken for AT and ES due to missing values for 2019. Y-axis indicates unweighted average annual wage decile. Age categories (low, medium, high) reflect terciles of workers' age distribution in 2011.

Figure A12: Wage deciles by AI (Webb) across countries



Notes: Values for the UK are excluded for data limitation reasons. 2018 wage values were taken for AT and ES due to missing values for 2019. Y-axis indicates unweighted average annual wage decile. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

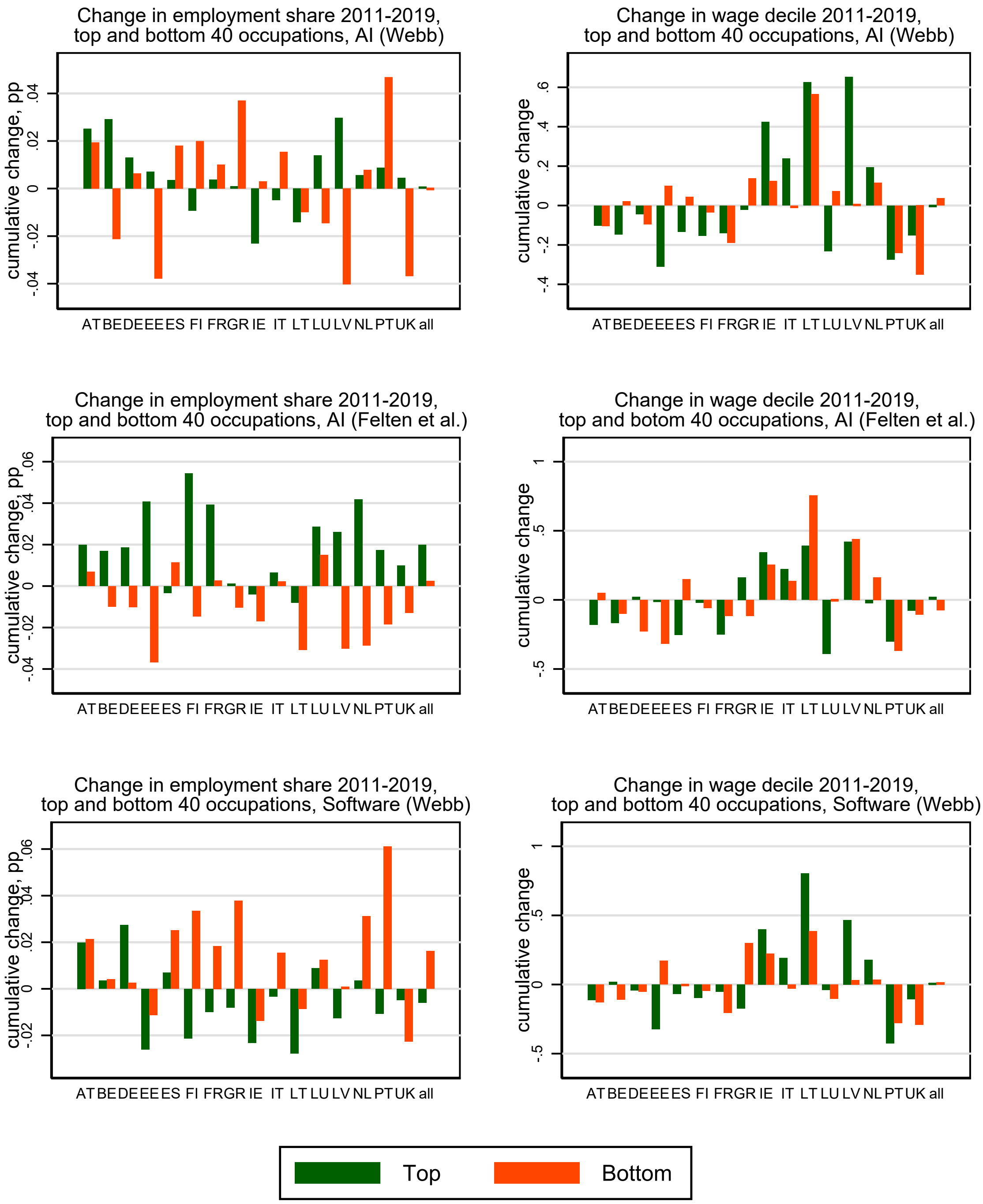
Figure A13: Wage deciles by AI (Felten et al.) across countries

Notes: Values for the UK are excluded for data limitation reasons. 2018 wage values were taken for AT and ES due to missing values for 2019. Y-axis indicates unweighted average annual wage decile. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

Figure A14: Wage deciles by software across countries

Notes: Values for the UK are excluded for data limitation reasons. 2018 wage values were taken for AT and ES due to missing values for 2019. Y-axis indicates unweighted average annual wage decile. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

Figure A15: Changes in employment shares and wage deciles



Notes: Top and bottom 40 occupations by technology measure. Changes in employment share are percentage points difference for the period 2011-2019. Changes in wages are difference in average income deciles for the period 2011-2019. For Austria, Spain and Lithuania 2018 wages values were taken instead of 2019. For Finland 2017 wages were taken instead of 2019. For the UK 2013 wages were taken instead of 2011. These changes were implemented due to limited availability of data for the reference years.

Appendix B

This appendix complements the evidence shown in Section 5.

Table B1: Change in employment vs. exposure to technology. Pooled sample 2011-2019

	(1)	(2)	(3)	(4)
AI, Webb	0.104***	0.111***	0.094***	0.192***
	(0.035)	(0.034)	(0.032)	(0.052)
Robot			-0.120***	
			(0.028)	
Software				-0.143***
				(0.042)
Observations	6767	6767	6767	6767
	(1)	(2)	(3)	(4)
AI, Felten	0.174***	0.174***	0.169**	0.175***
	(0.044)	(0.044)	(0.065)	(0.045)
Robot			-0.004	
			(0.044)	
Software				0.015
				(0.024)
Observations	5766	5766	5750	5750

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Dependent variable: within country cell's change in employment share from 2011 to 2019 winsorised at the top and bottom 1 percent. In columns (1) sector and country dummies included. In columns (2) sector*country dummies included. Columns (3) and (4) as (2) plus Software and Robots exposure measures respectively. Software and Robots are percentiles of exposure as in Webb (2020).

Table B2: ARTIFICIAL INTELLIGENCE. COUNTRIES. 2011-19. Change in employment vs. exposure to AI, Webb (AI_W)

	(1)	(2)	Younger (3)	Core (4)	Older (5)	LowESkill (6)	MedSkill (7)	HighSSkill (8)
AI, Webb	0.104***							
	(0.035)							
AI_W x AT		0.157***	0.332***	0.103***	0.015	-0.070	0.167***	0.041**
		(0.015)	(0.020)	(0.023)	(0.033)	(0.042)	(0.023)	(0.016)
AI_W x BE		0.206***	0.329***	0.226***	0.091***	-0.060**	0.069***	0.318***
		(0.010)	(0.018)	(0.006)	(0.019)	(0.023)	(0.018)	(0.020)
AI_W x DE		-0.021*	0.292***	-0.112***	-0.163***	0.409***	-0.122***	-0.341***
		(0.011)	(0.020)	(0.016)	(0.010)	(0.020)	(0.020)	(0.019)
AI_W x EE		0.207***	0.516***	0.310***	-0.177***	0.052	0.061**	0.238***
		(0.012)	(0.007)	(0.023)	(0.022)	(0.030)	(0.025)	(0.017)
AI_W x ES		0.053***	0.020	0.152***	0.081***	-0.014	-0.261***	0.263***
		(0.012)	(0.017)	(0.014)	(0.022)	(0.029)	(0.023)	(0.009)
AI_W x FI		0.186***	0.261***	0.257***	0.089**	-0.012	0.348***	-0.063**
		(0.015)	(0.017)	(0.032)	(0.030)	(0.038)	(0.022)	(0.025)
AI_W x FR		0.110***	0.117***	0.171***	0.104***	0.163***	-0.172***	0.089***
		(0.013)	(0.012)	(0.029)	(0.025)	(0.040)	(0.040)	(0.010)
AI_W x GR		-0.124***	-0.038*	-0.249***	0.040	-0.134	-0.396***	-0.064***
		(0.027)	(0.019)	(0.016)	(0.090)	(0.088)	(0.016)	(0.012)
AI_W x IE		-0.022*	0.040**	0.018	-0.087**	-0.054	-0.110***	-0.114***
		(0.012)	(0.019)	(0.013)	(0.031)	(0.039)	(0.022)	(0.015)
AI_W x IT		-0.016	0.080***	-0.163***	0.020	-0.074**	-0.061***	-0.087***
		(0.013)	(0.025)	(0.015)	(0.030)	(0.033)	(0.018)	(0.014)
AI_W x LT		0.000	-0.100***	0.316***	-0.174***	-0.481***	-0.002	0.408***
		(0.018)	(0.013)	(0.029)	(0.035)	(0.053)	(0.024)	(0.013)
AI_W x LU		0.225***	0.242***	0.418***	-0.027	-0.092***	-0.136***	0.523***
		(0.009)	(0.018)	(0.013)	(0.017)	(0.025)	(0.013)	(0.030)
AI_W x LV		0.175***	0.313***	0.089***	0.153***	0.019	0.077***	0.191***
		(0.012)	(0.014)	(0.023)	(0.018)	(0.044)	(0.014)	(0.016)
AI_W x NL		0.187***	0.204***	0.162***	0.190***	-0.078***	0.210***	0.010
		(0.009)	(0.013)	(0.015)	(0.020)	(0.025)	(0.019)	(0.011)
AI_W x PT		0.112***	0.365***	0.048**	-0.190***	0.193***	-0.307***	0.347***
		(0.013)	(0.017)	(0.018)	(0.032)	(0.039)	(0.023)	(0.007)
AI_W x UK		0.190***	0.279***	-0.013	0.263***	0.102***	0.055*	0.018
		(0.008)	(0.016)	(0.013)	(0.014)	(0.019)	(0.028)	(0.013)
Observations	6767	6767	2160	1653	2954	2145	1979	2641

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in employment share from 2011 to 2019 winsorised at the top and bottom 1 percent. The sub-sample in column (3), (4) and (5) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.The sub-samples in column (6) (7) and 8) consist of sector-occupation cells whose workers age was in the lower/middle and upper tercile respectively of the country's workers age distribution in 2011.

Table B3: ARTIFICIAL INTELLIGENCE. COUNTRIES. 2011-19. Wage changes vs. exposure to AI, Webb (AI_W)

	(1)	(2)	Younger (3)	Core (4)	Older (5)	LowSkill (6)	MedSkill (7)	HighSkill (8)
AI, Webb	0.002							
	(0.008)							
AI_W x AT		0.037***	0.011***	0.114***	0.004	0.017	0.040***	0.114***
		(0.004)	(0.003)	(0.010)	(0.011)	(0.011)	(0.007)	(0.009)
AI_W x BE		-0.025***	0.001	0.012***	-0.069***	-0.021***	-0.040***	-0.001
		(0.004)	(0.004)	(0.002)	(0.007)	(0.005)	(0.005)	(0.012)
AI_W x DE		0.005	0.036***	-0.052***	0.022***	0.007	0.004	0.034***
		(0.004)	(0.004)	(0.006)	(0.004)	(0.005)	(0.005)	(0.011)
AI_W x EE		-0.055***	0.057***	-0.122***	-0.131***	-0.046***	-0.056***	-0.047***
		(0.004)	(0.002)	(0.009)	(0.009)	(0.006)	(0.007)	(0.010)
AI_W x ES		-0.015***	-0.007**	-0.002	-0.026**	-0.005	-0.040***	-0.004
		(0.003)	(0.003)	(0.003)	(0.009)	(0.008)	(0.007)	(0.005)
AI_W x FI		0.003	-0.014***	0.071***	-0.028**	-0.049***	0.035***	0.047***
		(0.006)	(0.003)	(0.013)	(0.011)	(0.010)	(0.008)	(0.014)
AI_W x FR		-0.031***	-0.058***	0.026**	-0.056***	-0.009	-0.050***	0.057***
		(0.005)	(0.003)	(0.010)	(0.008)	(0.007)	(0.010)	(0.006)
AI_W x GR		-0.020**	0.045***	-0.130***	0.004	-0.108***	0.025***	-0.062***
		(0.007)	(0.003)	(0.008)	(0.028)	(0.020)	(0.004)	(0.007)
AI_W x IE		0.064***	0.029***	0.083***	0.074***	0.091***	0.041***	0.085***
		(0.003)	(0.004)	(0.005)	(0.010)	(0.010)	(0.006)	(0.009)
AI_W x IT		0.049***	0.047***	0.080***	0.056***	0.011	0.054***	0.077***
		(0.004)	(0.004)	(0.006)	(0.010)	(0.008)	(0.005)	(0.008)
AI_W x LT		0.038***	0.129***	-0.017**	0.019	-0.029**	0.104***	0.072***
		(0.005)	(0.003)	(0.006)	(0.013)	(0.011)	(0.007)	(0.006)
AI_W x LU		-0.065***	-0.044***	-0.083***	-0.064***	-0.046***	-0.083***	-0.083***
		(0.005)	(0.009)	(0.004)	(0.006)	(0.005)	(0.005)	(0.017)
AI_W x LV		0.081***	0.130***	0.029***	0.084***	-0.006	0.099***	0.220***
		(0.004)	(0.004)	(0.008)	(0.007)	(0.007)	(0.003)	(0.010)
AI_W x NL		-0.041***	-0.065***	-0.022***	-0.003	-0.072***	-0.039***	-0.068***
		(0.003)	(0.003)	(0.004)	(0.007)	(0.007)	(0.007)	(0.008)
AI_W x PT		0.026***	-0.029***	0.056***	0.061***	0.007	0.015**	0.044***
		(0.004)	(0.003)	(0.007)	(0.012)	(0.008)	(0.006)	(0.004)
AI_W x UK		-0.002	0.011*	-0.023***	0.025***	0.002	0.004	0.064***
		(0.003)	(0.005)	(0.005)	(0.006)	(0.005)	(0.009)	(0.008)
Observations	5793	5793	1784	1541	2468	1854	1671	2267

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Obs. are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in relative wages from 2011 to 2019 winsorised 1 percent top and bottom. Due to limited data availability for the reference years, 2018 wages values were taken for AT, ES and LT, and 2017 for FI instead of 2019. For the UK 2013 wages were taken instead of 2011. The sub-sample in column (3), (4) and (5) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.The sub-samples in column (6) (7) and 8) consist of sector-occupation cells whose workers age was in the lower/middle and upper tercile respectively of the country's workers age distribution in 2011.

Table B4: ARTIFICIAL INTELLIGENCE. COUNTRIES. 2011-19. Change in employment vs. exposure to AI, Felten (AI_F)

	(1)	(2)	Younger (3)	More (4)	Older (5)	LowSkill (6)	MedSkill (7)	HighSkill (8)
AI, Felten	0.174***							
	(0.044)							
AI_F x AT		0.238***	0.383***	0.143***	0.163***	-0.071*	-0.048	0.504***
		(0.012)	(0.021)	(0.029)	(0.011)	(0.035)	(0.031)	(0.010)
AI_F x BE		0.130***	0.187***	-0.150***	0.326***	-0.118**	-0.007	0.759***
		(0.012)	(0.034)	(0.008)	(0.018)	(0.047)	(0.025)	(0.039)
AI_F x DE		0.281***	0.385***	0.444***	0.113***	0.689***	0.623***	0.303***
		(0.011)	(0.026)	(0.022)	(0.008)	(0.037)	(0.024)	(0.012)
AI_F x EE		0.284***	0.531***	0.155***	-0.024**	0.346***	-0.047***	0.250***
		(0.017)	(0.044)	(0.036)	(0.010)	(0.079)	(0.007)	(0.023)
AI_F x ES		-0.040***	-0.021	-0.244***	0.084***	-0.174***	-0.112**	-0.285***
		(0.013)	(0.013)	(0.044)	(0.011)	(0.041)	(0.042)	(0.008)
AI_F x FI		0.267***	0.317***	0.263***	0.260***	-0.318***	0.154***	0.243***
		(0.012)	(0.007)	(0.040)	(0.012)	(0.065)	(0.029)	(0.058)
AI_F x FR		0.158***	0.074***	0.231***	0.250***	0.176***	-0.242***	0.121***
		(0.012)	(0.021)	(0.040)	(0.007)	(0.029)	(0.038)	(0.027)
AI_F x GR		0.091***	0.006	0.172***	0.034	0.802***	-0.832***	-0.142***
		(0.015)	(0.013)	(0.021)	(0.030)	(0.122)	(0.007)	(0.036)
AI_F x IE		-0.081***	-0.106***	-0.032	-0.148***	-0.820***	-0.321***	0.148***
		(0.014)	(0.024)	(0.029)	(0.020)	(0.054)	(0.019)	(0.019)
AI_F x IT		0.034**	-0.016	0.112***	-0.002	0.196***	-0.472***	0.065*
		(0.016)	(0.027)	(0.028)	(0.038)	(0.060)	(0.013)	(0.032)
AI_F x LT		-0.093***	-0.187***	-0.223***	0.110***	-0.807***	-0.250***	0.307***
		(0.013)	(0.012)	(0.044)	(0.014)	(0.082)	(0.017)	(0.024)
AI_F x LU		0.333***	0.544***	0.251***	-0.050	-0.467***	0.526***	0.836***
		(0.021)	(0.033)	(0.026)	(0.053)	(0.045)	(0.035)	(0.060)
AI_F x LV		0.008	-0.191***	0.239***	-0.032***	-0.499***	-0.256***	0.306***
		(0.012)	(0.035)	(0.032)	(0.009)	(0.064)	(0.009)	(0.037)
AI_F x NL		0.497***	0.498***	0.573***	0.435***	-0.223***	0.665***	0.929***
		(0.009)	(0.010)	(0.036)	(0.014)	(0.041)	(0.015)	(0.021)
AI_F x PT		0.559***	0.565***	0.433***	0.551***	0.408***	-0.211***	0.008
		(0.016)	(0.010)	(0.023)	(0.033)	(0.057)	(0.019)	(0.015)
AI_F x UK		0.154***	0.301***	0.045*	0.105***	-0.264***	-0.220***	0.014
		(0.010)	(0.027)	(0.023)	(0.012)	(0.050)	(0.025)	(0.027)
Observations	5766	5766	1828	1369	2569	1809	1632	2323

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in employment share from 2011 to 2019 winsorised at the top and bottom 1 percent. The sub-sample in column (3), (4) and (5) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.The sub-samples in column (6) (7) and 8) consist of sector-occupation cells whose workers age was in the lower/middle and upper tercile respectively of the country's workers age distribution in 2011.

Table B5: ARTIFICIAL INTELLIGENCE. COUNTRIES. 2011-19. Wage changes vs. exposure to AI, Felten (AI_F)

	(1)	(2)	Younger (3)	Core (4)	Older (5)	LowSkill (6)	MedSkill (7)	HighSkill (8)
AI, Felten	-0.015*							
	(0.008)							
AI_F x AT		-0.002	-0.019***	0.016	0.010***	0.022***	0.009	0.044***
		(0.003)	(0.005)	(0.010)	(0.003)	(0.006)	(0.011)	(0.003)
AI_F x BE		-0.041***	-0.024*	-0.082***	-0.024***	-0.003	-0.147***	-0.025
		(0.002)	(0.012)	(0.003)	(0.003)	(0.010)	(0.009)	(0.016)
AI_F x DE		0.038***	0.063***	0.020**	0.039***	0.050***	0.027***	-0.014***
		(0.003)	(0.010)	(0.009)	(0.002)	(0.011)	(0.008)	(0.002)
AI_F x EE		0.006	0.062***	-0.050**	-0.003	-0.087***	-0.019***	-0.156***
		(0.004)	(0.012)	(0.017)	(0.003)	(0.011)	(0.004)	(0.005)
AI_F x ES		-0.015***	-0.060***	0.003	0.001	-0.060***	-0.094***	0.023***
		(0.004)	(0.007)	(0.014)	(0.003)	(0.009)	(0.016)	(0.003)
AI_F x FI		0.038***	0.006**	0.065***	0.035***	0.044***	0.140***	0.067**
		(0.002)	(0.002)	(0.010)	(0.005)	(0.015)	(0.012)	(0.023)
AI_F x FR		-0.040***	-0.030***	-0.042***	-0.026***	0.125***	0.023**	-0.067***
		(0.003)	(0.005)	(0.012)	(0.002)	(0.006)	(0.008)	(0.011)
AI_F x GR		-0.042***	0.071***	-0.088***	-0.103***	-0.438***	0.020***	-0.056***
		(0.006)	(0.005)	(0.009)	(0.013)	(0.027)	(0.002)	(0.015)
AI_F x IE		-0.010**	0.053***	0.006	-0.086***	-0.073***	0.093***	0.148***
		(0.004)	(0.009)	(0.010)	(0.007)	(0.008)	(0.006)	(0.008)
AI_F x IT		-0.029***	-0.052***	-0.018**	-0.001	-0.017	0.057***	0.005
		(0.004)	(0.007)	(0.008)	(0.011)	(0.010)	(0.004)	(0.013)
AI_F x LT		-0.049***	0.016***	-0.133***	-0.016***	-0.185***	-0.008	0.181***
		(0.004)	(0.005)	(0.015)	(0.004)	(0.016)	(0.006)	(0.010)
AI_F x LU		-0.059***	0.002	-0.038***	-0.171***	0.062***	-0.064**	-0.227***
		(0.009)	(0.014)	(0.010)	(0.010)	(0.007)	(0.026)	(0.025)
AI_F x LV		-0.008*	0.062***	-0.034**	-0.052***	-0.130***	0.153***	0.307***
		(0.004)	(0.011)	(0.016)	(0.003)	(0.011)	(0.001)	(0.014)
AI_F x NL		-0.009***	-0.019***	-0.014	0.013***	-0.050***	0.045***	-0.312***
		(0.003)	(0.006)	(0.013)	(0.003)	(0.006)	(0.008)	(0.011)
AI_F x PT		0.006	-0.023***	0.027**	0.029***	-0.031**	0.104***	0.147***
		(0.004)	(0.005)	(0.009)	(0.007)	(0.013)	(0.006)	(0.007)
AI_F x UK		-0.025***	0.023*	-0.035***	-0.060***	-0.009	-0.024*	0.098***
		(0.003)	(0.012)	(0.006)	(0.004)	(0.007)	(0.013)	(0.009)
Observations	4922	4922	1511	1268	2143	1565	1362	1994

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Obs. are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in relative wages from 2011 to 2019 winsorised 1 percent top and bottom. Due to limited data availability for the reference years, 2018 wages values were taken for AT, ES and LT, and 2017 for FI instead of 2019. For the UK 2013 wages were taken instead of 2011. The sub-sample in column (3), (4) and (5) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.The sub-samples in column (6) (7) and 8) consist of sector-occupation cells whose workers age was in the lower/middle and upper tercile respectively of the country's workers age distribution in 2011.

Table B6: Change in employment vs. exposure to Software. Pooled sample. 2000-2010 vs 2011-2019.

	All	LowAgeg	MedAgeg	HighAgeg	LowSkill	MedSkill	HighSkill
Software 2011-2019	-0.025	0.107***	-0.083*	-0.117**	0.004	-0.032	0.044
	(0.020)	(0.032)	(0.046)	(0.050)	(0.040)	(0.049)	(0.036)
Observations	6767	2160	1653	2954	2145	1979	2641
Software 2000-2010	-0.171***	0.134*	-0.124	-0.165*	-0.004	-0.104	0.053
	(0.054)	(0.071)	(0.081)	(0.084)	(0.097)	(0.120)	(0.104)
Observations	5039	1709	1260	2070	1639	1460	1932

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in employment share from 2011 to 2019 and 2000-2010 respectively winsorised at the top and bottom 1 percent. The sub-sample in column (3), (4) and (5) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.The sub-samples in column (6) (7) and 8) consist of sector-occupation cells whose workers age was in the lower/middle and upper tercile respectively of the country's workers age distribution in 2011.

Table B7: SOFTWARE. COUNTRIES. 2011-19. Change in employment vs. exposure to software, Webb

	(1)	(2)	LowAgeg (3)	MedAgeg (4)	HighAgeg (5)	LowSkill (6)	MedSkill (7)	HighSkill (8)
Software Exp	-0.025							
	(0.020)							
Software x AT		0.031**	0.192***	-0.021	-0.120***	-0.003	0.120***	0.003
		(0.014)	(0.025)	(0.030)	(0.039)	(0.023)	(0.024)	(0.017)
Software x BE		0.066***	0.212***	0.145***	-0.161***	-0.079***	0.013	-0.020
		(0.012)	(0.026)	(0.016)	(0.016)	(0.015)	(0.014)	(0.017)
Software x DE		0.117***	0.283***	-0.077**	0.071***	0.244***	0.276***	-0.110***
		(0.011)	(0.018)	(0.030)	(0.021)	(0.014)	(0.023)	(0.014)
Software x EE		-0.060***	0.168***	-0.148***	-0.136***	-0.082***	0.089***	0.396***
		(0.014)	(0.033)	(0.039)	(0.031)	(0.021)	(0.023)	(0.019)
Software x ES		0.011	-0.033	0.278***	-0.055	-0.028	-0.203***	0.170***
		(0.014)	(0.020)	(0.043)	(0.032)	(0.023)	(0.022)	(0.012)
Software x FI		-0.058***	0.133***	-0.189***	-0.248***	-0.087***	0.175***	-0.086***
		(0.014)	(0.019)	(0.039)	(0.033)	(0.025)	(0.015)	(0.017)
Software x FR		0.005	0.109***	-0.085**	-0.015	0.236***	-0.182***	-0.091***
		(0.012)	(0.017)	(0.033)	(0.031)	(0.030)	(0.047)	(0.010)
Software x GR		-0.124***	-0.122***	-0.365***	0.233***	-0.037	-0.204***	-0.036*
		(0.023)	(0.016)	(0.030)	(0.075)	(0.073)	(0.016)	(0.017)
Software x IE		-0.011	0.184***	-0.107***	-0.163***	0.041	-0.051**	-0.091***
		(0.014)	(0.019)	(0.033)	(0.043)	(0.025)	(0.020)	(0.008)
Software x IT		-0.080***	0.079**	-0.359***	-0.122**	0.087***	-0.188***	-0.187***
		(0.014)	(0.028)	(0.025)	(0.042)	(0.025)	(0.018)	(0.017)
Software x LT		0.038**	0.122***	0.212***	-0.267***	-0.361***	0.049*	0.256***
		(0.017)	(0.023)	(0.042)	(0.048)	(0.040)	(0.026)	(0.015)
Software x LU		-0.103***	-0.098***	0.016	-0.142***	-0.076***	-0.284***	0.275***
		(0.010)	(0.021)	(0.014)	(0.015)	(0.023)	(0.012)	(0.010)
Software x LV		0.025*	0.359***	0.017	-0.187***	-0.295***	0.133***	0.082***
		(0.014)	(0.037)	(0.043)	(0.026)	(0.030)	(0.016)	(0.019)
Software x NL		-0.105***	0.053***	-0.322***	-0.143***	0.017	0.018	-0.073***
		(0.010)	(0.012)	(0.025)	(0.026)	(0.018)	(0.013)	(0.009)
Software x PT		-0.199***	0.006	-0.251***	-0.544***	0.229***	-0.223***	0.202***
		(0.015)	(0.020)	(0.036)	(0.040)	(0.037)	(0.018)	(0.014)
Software x UK		0.041***	0.101***	-0.158***	0.114***	0.101***	0.114***	0.085***
		(0.012)	(0.017)	(0.023)	(0.027)	(0.019)	(0.022)	(0.010)
Observations	6767	6767	2160	1653	2954	2145	1979	2641

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in employment share from 2011 to 2019 winsorised at the top and bottom 1 percent. The sub-sample in column (3), (4) and (5) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.The sub-samples in column (6) (7) and 8) consist of sector-occupation cells whose workers age was in the lower/middle and upper tercile respectively of the country's workers age distribution in 2011.

Table B8: SOFTWARE. COUNTRIES. 2011-19. Wage changes vs. exposure to software, Webb

	(1)	(2)	Younger (3)	Core (4)	Older (5)	LowSkill (6)	MedSkill (7)	HighSkill (8)
Software Exp	0.011							
	(0.010)							
Software x AT		0.011**	0.004	0.041***	-0.017	-0.008	-0.018**	0.070***
		(0.005)	(0.003)	(0.011)	(0.013)	(0.007)	(0.008)	(0.009)
Software x BE		-0.005	0.011	0.057***	-0.075***	-0.029***	-0.041***	0.005
		(0.005)	(0.007)	(0.007)	(0.007)	(0.004)	(0.005)	(0.010)
Software x DE		-0.038***	-0.001	-0.079***	-0.055***	-0.070***	0.009	0.010
		(0.004)	(0.003)	(0.011)	(0.007)	(0.003)	(0.007)	(0.009)
Software x EE		-0.044***	0.014**	-0.038**	-0.122***	0.016**	-0.095***	0.025**
		(0.006)	(0.005)	(0.015)	(0.010)	(0.007)	(0.005)	(0.010)
Software x ES		-0.021***	0.010***	-0.049***	-0.035***	-0.015*	-0.067***	-0.013*
		(0.004)	(0.002)	(0.013)	(0.011)	(0.007)	(0.006)	(0.007)
Software x FI		-0.007	0.004	0.013	-0.036**	0.005	-0.059***	0.017*
		(0.006)	(0.003)	(0.013)	(0.013)	(0.008)	(0.007)	(0.009)
Software x FR		-0.010*	-0.043***	0.044***	-0.027**	-0.017***	-0.065***	0.040***
		(0.005)	(0.002)	(0.011)	(0.010)	(0.005)	(0.012)	(0.005)
Software x GR		-0.005	0.051***	-0.092***	-0.009	-0.111***	0.017***	-0.082***
		(0.008)	(0.002)	(0.012)	(0.026)	(0.019)	(0.004)	(0.009)
Software x IE		0.032***	0.001	0.036***	0.049***	0.040***	-0.025***	0.023***
		(0.005)	(0.002)	(0.010)	(0.014)	(0.008)	(0.008)	(0.005)
Software x IT		0.069***	0.071***	0.101***	0.051***	0.016*	0.024***	0.102***
		(0.005)	(0.003)	(0.009)	(0.013)	(0.008)	(0.005)	(0.009)
Software x LT		0.087***	0.133***	0.078***	0.066***	-0.059***	0.123***	0.130***
		(0.007)	(0.003)	(0.011)	(0.017)	(0.011)	(0.006)	(0.007)
Software x LU		-0.023***	-0.016**	-0.056***	0.038***	-0.048***	-0.003	-0.030***
		(0.003)	(0.005)	(0.007)	(0.006)	(0.004)	(0.004)	(0.005)
Software x LV		0.125***	0.154***	0.087***	0.207***	0.030***	0.035***	0.362***
		(0.006)	(0.007)	(0.014)	(0.008)	(0.006)	(0.004)	(0.012)
Software x NL		-0.023***	-0.031***	-0.017*	0.007	-0.026***	-0.047***	0.006
		(0.004)	(0.003)	(0.008)	(0.009)	(0.005)	(0.006)	(0.005)
Software x PT		0.019***	-0.007***	0.043***	0.008	0.043***	-0.014***	0.001
		(0.005)	(0.002)	(0.014)	(0.012)	(0.007)	(0.004)	(0.008)
Software x UK		0.033***	0.034***	0.014	0.075***	-0.006	0.048***	0.047***
		(0.004)	(0.003)	(0.008)	(0.009)	(0.004)	(0.009)	(0.005)
Observations	5793	5793	1784	1541	2468	1854	1671	2267

Notes: Linear regression. Robust standard errors in parentheses, clustered by country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country cell's change in relative wages from 2011 to 2019 winsorised 1 percent top and bottom. Due to limited data availability for the reference years, 2018 wages values were taken for AT, ES and LT, and 2017 for FI instead of 2019. For the UK 2013 wages were taken instead of 2011. The sub-sample in column (3), (4) and (5) consist of sector-occupation cells whose average educational attainment is in the lower, middle and upper tercile respectively of country's education distribution.The sub-samples in column (6) (7) and 8) consist of sector-occupation cells whose workers age was in the lower/middle and upper tercile respectively of the country's workers age distribution in 2011.

Glossaries

Country Codes

AT Austria

BE Belgium

DE Germany

EE Estonia

ES Spain

FI Finland

FR France

GR Greece

IE Ireland

IT Italy

LT Lithuania

LU Luxembourg

LV Latvia

NL The Netherlands

PT Portugal

UK United Kingdom

Occupational Codes

111 Legislators and senior officials

112 Managing directors and chief executives

121 Business services and administration managers

122 Sales, marketing and development managers

131 Production managers in agriculture, forestry and fisheries

132 Manufacturing, mining, construction, and distribution managers

133 Information and communications technology service managers

134 Professional services managers

141 Hotel and restaurant managers

142 Retail and wholesale trade managers

143 Other services managers

211 Physical and earth science professionals

212 Mathematicians, actuaries and statisticians

213 Life science professionals

214 Engineering professionals (excluding electrotechnology)

215 Electrotechnology engineers

216 Architects, planners, surveyors and designers

221 Medical doctors

222 Nursing and midwifery professionals

223 Traditional and complementary medicine professionals

224 Paramedical practitioners

225 Veterinarians

226 Other health professionals

231 University and higher education teachers

232 Vocational education teachers

233 Secondary education teachers

234 Primary school and early childhood teachers

235 Other teaching professionals

241 Finance professionals

242 Administration professionals

243 Sales, marketing and public relations professionals

251 Software and applications developers and analysts

252 Database and network professionals

261 Legal professionals

262 Librarians, archivists and curators

263 Social and religious professionals

264 Authors, journalists and linguists

265 Creative and performing artists

311 Physical and engineering science technicians

312 Mining, manufacturing and construction supervisors

313 Process control technicians

314 Life science technicians and related associate professionals

315 Ship and aircraft controllers and technicians

321 Medical and pharmaceutical technicians

322 Nursing and midwifery associate professionals

323 Traditional and complementary medicine associate professionals

324 Veterinary technicians and assistants

325 Other health associate professionals

331 Financial and mathematical associate professionals

332 Sales and purchasing agents and brokers

333 Business services agents

334 Administrative and specialized secretaries

335 Regulatory government associate professionals

341 Legal, social and religious associate professionals

342 Sports and fitness workers

343 Artistic, cultural and culinary associate professionals

351 Information and communications technology operations and user support technicians

352 Telecommunications and broadcasting technicians

411 General office clerks

412 Secretaries (general)

413 Keyboard operators

421 Tellers, money collectors and related clerks

422 Client information workers

431 Numerical clerks

432 Material-recording and transport clerks

441 Other clerical support workers

511 Travel attendants, conductors and guides

512 Cooks

513 Waiters and bartenders

514 Hairdressers, beauticians and related workers

515 Building and housekeeping supervisors

516 Other personal services workers

521 Street and market salespersons

522 Shop salespersons

523 Cashiers and ticket clerks

524 Other sales workers

531 Child care workers and teachers' aides

532 Personal care workers in health services

541 Protective services workers

611 Market gardeners and crop growers

612 Animal producers

613 Mixed crop and animal producers

621 Forestry and related workers

622 Fishery workers, hunters and trappers

634 Subsistence fishers, hunters, trappers and gatherers

711 Building frame and related trades workers

712 Building finishers and related trades workers

713 Painters, building structure cleaners and related trades workers

721 Sheet and structural metal workers, moulders and welders, and related workers

722 Blacksmiths, toolmakers and related trades workers

723 Machinery mechanics and repairers

731 Handicraft workers

732 Printing trades workers

741 Electrical equipment installers and repairers

742 Electronics and telecommunications installers and repairers

751 Food processing and related trades workers

752 Wood treaters, cabinet-makers and related trades workers

753 Garment and related trades workers

754 Other craft and related workers

811 Mining and mineral processing plant operators

812 Metal processing and finishing plant operators

813 Chemical and photographic products plant and machine operators

814 Rubber, plastic and paper products machine operators

815 Textile, fur and leather products machine operators

816 Food and related products machine operators

817 Wood processing and papermaking plant operators

818 Other stationary plant and machine operators

821 Assemblers

831 Locomotive engine drivers and related workers

832 Car, van and motorcycle drivers

833 Heavy truck and bus drivers

834 Mobile plant operators

835 Ships' deck crews and related workers

911 Domestic, hotel and office cleaners and helpers

912 Vehicle, window, laundry and other hand cleaning workers

921 Agricultural, forestry and fishery labourers

931 Mining and construction labourers

932 Manufacturing labourers

933 Transport and storage labourers

941 Food preparation assistants

952 Street vendors (excluding food)

961 Refuse workers

962 Other elementary workers

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