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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, 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. 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 relative wages across occupations and potential exposures to new technologies.

Keywords: artificial intelligence, employment, skills, occupations

JEL codes: J23, O33

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1 Introduction

Waves of automation have usually been accompanied by anxiety about the future of jobs. This apprehension persists, even though history suggests that previous fears about labour becoming substituted by machines were often overstated (e.g. Autor (2015), Bessen (2019)). In fact, the potential negative effects of technology on employment have historically been counterbalanced by increases in productivity and production, and creation of new tasks and jobs. Whether the same can be expected from the current new wave of technological innovation, characterised by artificial intelligence (AI) breakthroughs, remains an open question.

AI breakthroughs include advancement in robotics, supervised and unsupervised learning, natural language processing, machine translation and image recognition, to name only a few. These are deep learning and machine learning applications, based on algorithms that learn to perform tasks by following statistical patterns in data, rather than following human instructions. Thus, AI is generating a general-purpose technology that enables automation of human labour in non-routine tasks, both in manufacturing and services – from providing medical advice to writing programming codes. It stands in contrast to other technologies such as computerisation and industrial robots that enable automation in a limited set of manual tasks. AI is experiencing fast growth and diffusion (e.g. Agrawal et al. (2018)), the most recent development being generative AI, such as ChatGPT, that uses deep learning and machine learning techniques to generate new contents and perform creative tasks, such as images, music, and text. Thus, the debate about the potential impact of technologies on jobs has been revived (see for example Ford (2015), Frey and Osborne (2017), Susskind (2020) and Acemoglu and Restrepo (2020b)).

The leading theories explaining the main transmission mechanisms of technological changes on labour market outcomes are the so-called Skill Biased Technological Change (SBTC) and Routinisation theories. Both highlight a heterogeneous impact of technology on employment and wages of workers with different skills. 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) and vom Lehn (2020)).[1]

As other technological innovations, automation, including AI-enabled automation, may impact overall aggregate employment and wages, as well as the wage and employment distributions, 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 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 (e.g. Bessen (2019)). An important novelty about AI is that it enables automation of non-routine tasks performed by high-skilled workers, thus the complementarity between AI and high-skilled workers, which is at the heart of SBTC, can no longer be taken for granted.

The empirical evidence on the effect of AI-enabled technologies on jobs and wages is still evolving, and to date focuses mostly on the United States. To assess 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 the goal of measuring its 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

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

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-enabled technologies and employment shares and relative wages by occupations in 16 European countries over the period 2011-2019. These years saw the rise of deep learning applications such as language processing, image recognition, algorithm-based recommendations or fraud detection. Though more limited in scope than the current generative AI models such as ChatGPT, deep learning applications are nonetheless revolutionary, and still trigger concerns about the impact on jobs.[2]

We use data at 3-digit occupation level (according to the International Standard Classification of Occupations) from the Eurostat's Labour Force Survey and two proxies of potential AI-enabled automation, borrowed from the literature. The first proxy is the AI Occupational Impact created by Felten et al. (2018) and Felten et al. (2019), and the second one is the measure of the exposure of tasks and occupations to AI, constructed by Webb (2020). We interpret both measures as proxies to potential exposure to 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

[2]Our analysis does not include the most recent developments in generative AI due to data limitations. For specific analysis of the potential labour market impact of large language models we refer the reader to Felten et al. (2023), Eloundou et al. (2023), Gmyrek et al. (2023) and Korinek (2023).

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 occupations in 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 found for the pooled European countries is driven by jobs that employ high-skilled workers, in line with the complementarity between human labour and technology stressed by 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 compare exposure to AI with previous technologies, we perform a similar analysis for software-enabled automation using the occupational measure of software exposure by Webb (2020). We do not find a strong relationship between software and employment shares for Europe during 2011 and 2019, the period of analysis. This stands in contrast with our results for AI. Nevertheless, drawing conclusions in terms of polarisation would require a deeper analysis.

Our results should not be interpreted as claims on causal effects of technology on labour market outcomes. We believe that their identification is only possible by firm event studies in highly controlled environments. Instead, the value of our results should be assessed as evidence on the statistical association between potential exposure of employment by occupations to AI innovations and the degree of complementarity or substitution between them. We support our interpretation of these associations in a battery of robustness checks that distinguish between sectors, occupations and alternative measurement of exposure to AI.

In sum, our findings support the view 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. Nevertheless, two notes of caution are in order: i) it is too early to foresee the scope and applicability of the latest wave of AI technologies, and ii) our analysis, by its own nature, is silent on effects of AI on *aggregate* employment and wages.

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 discusses the empirical strategy and the results. Section 5 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, $o_{i,t}$ $i \in (1, I)$, which produce intermediate inputs used in the production of the final good y_t, are combinations of tasks for each occupation i, $s_i \in (1, J_{i,t})$, :

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

$$o_{i,t} = \left[\sum_{j=1}^{J_{i,t}} \beta_{i,j} s_{i,j,t}^{\sigma_i} \right]^{1/\sigma_i} \tag{2}$$

with I being the number of occupations, $J_{i,t}$ denotes the number of productive tasks at each moment in time t that are performed by occupation i, α_i the weight of occupation i in the production of the final good, $\beta_{i,j}$ the weight of task j in occupation i, and $1/(1-\rho)$ and $1/(1-\sigma_i)$ the elasticities of substitution among occupations and skills in occupation i, respectively.

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

A fully automated task in occupation i, $j \in A_{i,t}$, can be performed without human labour:

$$s_{i,j,t} = \lambda_{i,j,t} M_{i,j,t} \tag{3}$$

$\lambda_{i,j,t}$ being the relative productivity of machines versus labour in task j and occupation i.

Labour in occupation i is employed in the rest of tasks, $j \in J_{i,t} - A_{i,t}$, which need to be performed using both machines ($M_{i,j,t}$) and labour ($L_{i,t}$):

$$s_{i,j,t} = L_{i,t}^{\mu_i} [\lambda_{i,j,t} M_{i,j,t}]^{1-\mu_i} \tag{4}$$

$\mu_i \in (0,1)$ controls input shares in occupations of the labour intensive sector. The relative price of machines is q_t. Supplies of labour and machines are predetermined. Full automation is feasible for a given task when technology is more productive than labour, i.e., $\lambda_{i,j,t} > q_t/W_{i,t}$, where $W_{i,t}$ is the wage paid to labour in occupation i at time t. For simplicity we assume that innovation and the relative price of machines, q_t, are exogenous, and that the size of the total set of tasks, $J_{i,t}$, and of the set of automated tasks, $A_{i,t}$, grow at the same (exogenous) rate in all occupations.[3]

Given the simple Cobb-Douglas structure of the production function of non-automated tasks, it is straightforward to derive relative labour demand equations for each occupation i:

$$\frac{L_{i,t}^d}{L_t^d} = \frac{\sum_{j \in I_t - A_{i,t}} \frac{\mu_i s_{i,j,t}^d}{W_{i,t}}}{\sum_{i \in I} \sum_{j \in I_t - A_{i,t}} \frac{\mu_i s_{i,j,t}^d}{W_{i,t}}} \tag{5}$$

where $s_{i,j,t}^d$ is demand for task j in 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:

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

$$W_{i,t} = \kappa_i \left[\frac{o_{i,t}}{L_{i,t}} + \delta_i + \gamma_i \right] \tag{6}$$

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 (5) and (6), 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-aged 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 provide 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 assesses two different technologies, namely AI-enabled technologies and software, thereby further contributing to the existing literature, which mostly tends to focus on the impact of one type of technology only.[4]

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. Subsection 3.1 presents the data sources, subsection 3.2 describes the construction of sector-occupation cells for which potential exposure to AI is being measured, and subsection 3.3 then shows the final score representing exposure to AI of the occupations in our sample.

3.1 Data Sources and Technology Measures

We now describe our data for employment and wages, and the technology exposure measures used throughout this paper.

Labour market data For harmonised employment, wage and worker characteristics information we use the EU Labour Force Survey (EU-LFS), annual microdata, for the period 2011-2019. This survey provides details on cross-country labour force compositions. 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 of employment: agriculture, construction, financial services, services, manufacturing and public

[4]Two notable exceptions are Webb (2020) and Acemoglu et al. (2022).
[5]We exclude armed forces occupations from our sample.

services.[6]

For **wages**, we use the monthly pay from the main job, which the cross-country 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 individual data on wage deciles. We further focus on worker characteristics such as age and skills. We proxy skills with education of workers, which is measured as the highest educational attainment using the International Standard Classification of Education (ISCED).

Technology exposure measures We adopt a total of three existing measures from the literature: two for occupations' exposure to AI and one for software exposure. Using a selection of different technology exposure measures allows us to better capture the complexity and variety of aspects of technological progress that impact workers.

The first AI measure is the **AI Occupational Impact (AIOI) scores** developed by Felten et al. (2018), which we will also refer to as AI *(Felten et al.)*.[7] This measure links advances in AI applications to the skill characteristics by occupation to measure how much AI could affect each occupation. These scores are based on backward-looking AI progress between 2010 and 2015, which are then tied to occupations based on their descriptions from 2019 O*NET data. O*NET provides a total of 52 distinct abilities and information on the prevalence and importance of each ability per occupation.[8] The measured AI progress comes from the Electronic Frontier Foundation AI Progress Measurement dataset. 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. The authors then link the identified AI applications from the AI progress database to the 52 available abilities from O*NET using survey responses from Amazon's Mechanical Turk (mTurk). The final aggregated occupational technology exposure score is computed by weighting 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

[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).

[7]Actual scores are taken from Felten et al. (2019).

[8]Examples for such abilities are "verbal abilities", "physical strength abilities" or "visual abilities". Each of the 52 abilities is part of one of four broader groups of abilities: cognitive, physical, psychomotor and sensory abilities. The full list of abilities can be viewed here: https://www.onetonline.org/find/descriptor/browse/1.A.

sample. A higher AIOI score corresponds to a greater exposure of the occupation (through the workers' abilities that it requires) to AI advancements that occurred between from 2010 to 2015. Note that even though this AI measure is based on AI progress from 2010 to 2015, it might also indirectly pick up AI progress from preceding years; this is the case if AI progress on certain applications between 2010 and 2015 correlates positively with the AI progress on the same applications in previous years.

The second **AI exposure measure and the software exposure measure** are taken from Webb (2020). These scores of occupations' exposure to technology are constructed by quantifying the textual overlap (verb-noun pairs) of patents (taken from Google Patents Public Data) using natural language processing to job descriptions from O*NET. The idea here is to assess to what extent patented technologies are suited to perform tasks of a given occupation. The measured technology exposure with these indicators highlights how labour might be "displaced" by technological advancements that tackle specific tasks of occupations. 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). Therefore, these two measures affect workers of different skill levels across different occupations.[9]

Both AI measures (Felten et al. and Webb) indicate the *potentiality* of AI impact on given occupations, rather than materialised AI impact, but the AI measures slightly differ in the way they capture the applicability of AI to a task. The AI measure by Felten et al. is fundamentally driven by the exposure of workers' abilities to technological advancements, whereas the measure by Webb highlights the availability of machine learning algorithms that are aligned with occupations' tasks. These differences in construction allow us to identify a broader range of the complex impact of AI technologies. As a result, the two different AI measures return slightly different scores for how much a given occupation is exposed to AI (how this is done is explained more in subsection 3.2). Ranking occupations from high to low exposure, the difference in what our two AI measures capture becomes apparent: The measure by Felten et al. ranks professional occupations that require strong technical knowledge such as mathematicians, finance professionals or software developers as highly exposed to

[9] Webb (2020) finds this for SOC-classified occupations, and we confirm this finding for ISCO-classified occupations, shown in Subsection 3.3.

AI. Occupations requiring manual labour (e.g., cleaners, manufacturers, painters) are ranked low, capturing that limitations of algorithms performing manual tasks. By contrast, the AI measure by Webb ranks many occupations in agriculture as highly exposed to AI technologies, while sales and teaching occupations are ranked low, capturing the vast technological advancements and opportunities in agriculture (e.g., Tzachor et al. (2022), Cole et al. (2018), Rose and Chilvers (2018)). Note that this is not an artefact of our conversion to ISCO occupations, but that these trends are the same for SOC-classified occupations (see e.g., Acemoglu et al. (2022) who compares these measures for SOC occupations). Instead, this highlights the different emphasis of the measures; using both measures gives us a more flexible definition of AI, thus allowing us to better understand the complex impact of AI on occupation. Subsection 3.3 describes in detail the extent to which occupations (and ultimately employment) are potentially exposed to technological progress.

3.2 Our merged 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 countries because we transform the raw scores (at 3-digit ISCO) into percentiles weighted by the occupation-sector cells employment.[10]

In 2011, there was a break in the ISCO classification (from ISCO88 to ISCO08). This re-classification 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.

3.3 How exposed are occupations to new technologies?

This subsection highlights how occupations, and ultimately employment in Europe, are affected by AI and software according to the technology measures described above.

Technology exposure of occupations 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 slightly fewer occupation (only 104

[10] 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.

distinct occupations in our data set) and averages by construction at 0.5 with a standard deviation of 0.26. Table 1 provides summary statistics of our three technology measures based on the considered occupations.

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

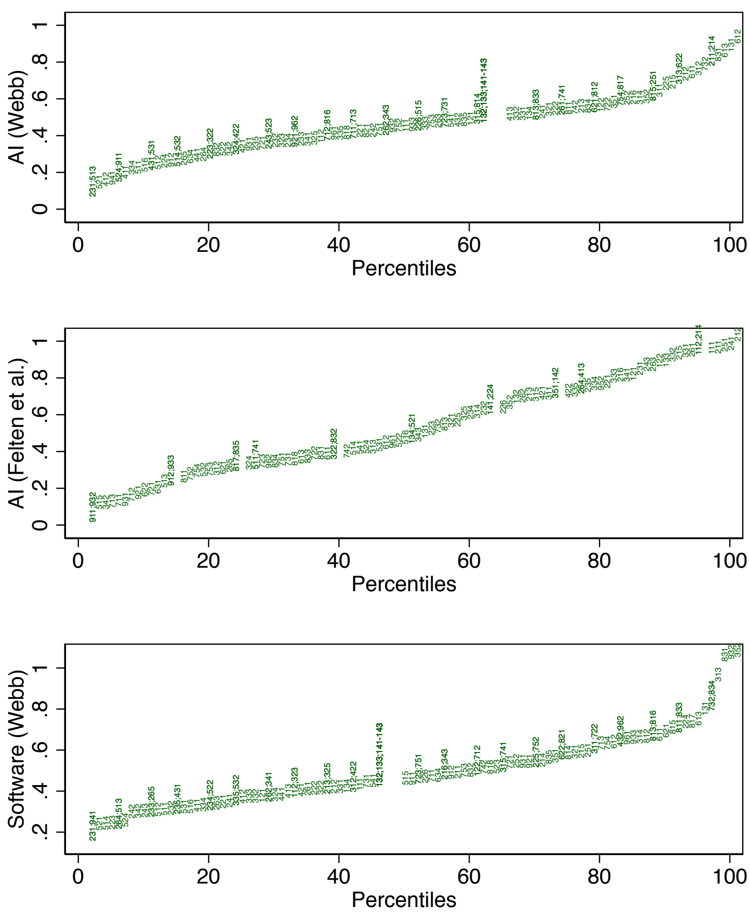
Notes: Summary statistics of technology measures across all available occupations (unweighted). N corresponds to the number of distinct occupations in our data set, for which the technology measure provides a value.

To get a better idea of how the available occupations compare to each other with respect to their potential technology exposure, we rank them by their scores for each technology measure. Figure 1 shows these detailed distributions, and further provides Spearman's rank correlations to indicate how the three technology measures correlate. Two facts stand out:

First, depending on the technology measure used, different occupations are ranked at the very top and bottom. Table 2 zooms in on the exact top and bottom five occupations by each measure, and provides their respective technology scores. Interestingly, 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. This means, there is a discrepancy between the measures as to which occupations are most and least exposed to the potential impact of new technologies. This likely comes as expected when comparing potential software exposure to AI exposure, but might perhaps be more surprising when comparing the two different AI exposure measures. However, this results from the differences in how the two AI measures are computed (as described in Subsection 3.1), and consequently, what aspects of AI progress they capture. Therefore, the fact that different occupations are highlighted as being potentially exposed to AI advancements is not only unsurprising, but also desired as it allows us to capture a more complete picture of how the technology might impact labour. Accordingly, we expect empirical results to vary slightly between the two AI measures, also capturing the degree of uncertainty to which occupations' exposure to technology is measured.

Second, despite this discrepancy in most and least exposed occupations, the overall rankings of occupations by the two measures of the potential impact of AI are quite similar. Spearman's rank correlations at the bottom of Figure 1 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, Webb's software measure and Felten et al.'s AI measure are negatively correlated ($r_s = -0.29$), which signals that new AI technologies are not only about the application of software, and highlights that AI and digitalisation, as captured by the software measure, may impact jobs differently.

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	1.00	
	(0.04)		
Software (Webb)	0.64	-0.29	1.00
	(0.00)	(0.00)	

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.

Technology exposure of workers Who are the workers that are in occupations exposed to new technologies? Generally, workers with higher education are found in occupations with higher AI technology scores and lower software scores compared to less educated workers.[11] Workers' age seems less obviously linked to technology exposure: all three age categories (low, medium and high age) are on average similarly exposed to all technology measures.[12] Table A1 in the Appendix gives an overview of technology measures and workers, showing the average percentile of each technology measure by worker characteristics (i.e. education and age).

How did the characteristics of workers change between 2011 and 2019? 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). Table A2 in the Appendix shows all the employment shares in 2011 and 2019 by the respective change by worker demographics (i.e. education and age), as well as the change in employment shares over time.

What happened to the average wage deciles by worker characteristics between 2011 and 2019? The average wage decile slightly increased for all skill and age groups, with the young and low-skilled workers seeing the highest increases in their average wage decile (by 0.24 and 0.26, respectively), and the old and high-skilled seeing the lowest increases (by 0.14 and 0.12, respectively). See Table A3 and Figures A1 and A2 in the Appendix for details of these observations for employment shares and wage deciles respectively.

Technology exposure of employment To gauge the potential exposure of the overall workforce to new technologies, what matters is the occupational composition of total employment, and importantly, changes to employment. So, how did employment in occupations

[11]Education categories reflect terciles of workers' educational attainment distribution in a given country in 2011. Note that educational terciles are also referred to as skill terciles in this paper.

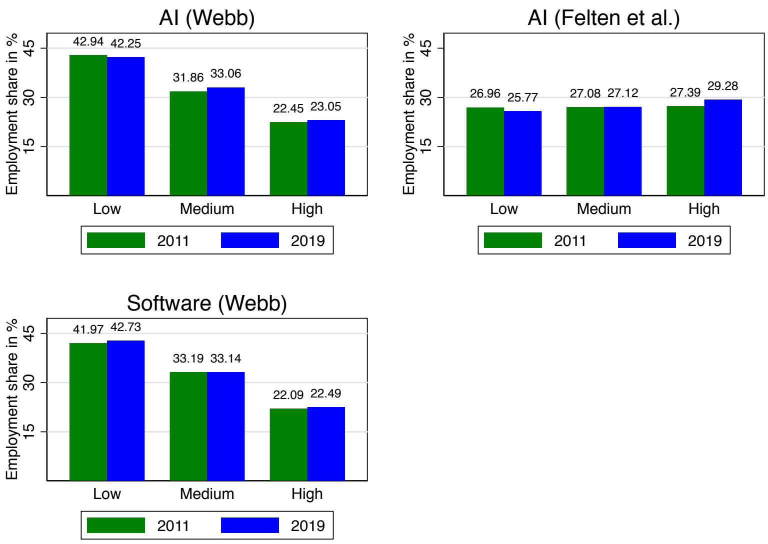
[12]Similar to skills, we divide workers into three age groups , which reflect respective terciles of workers' age distribution in 2011.

change by technology exposure? While there are differences across technology measures, employment shares generally increased slightly for high-scoring occupations (this pattern is least pronounced for the software measure). 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. Again highlighting the different aspects of AI that these measures are picking up. Overall, these data reveal that about 25% of all jobs in these European countries were in occupations highly exposed to AI and that the shares of employment in these jobs increased more than in the lowest exposed jobs. Interestingly, when looking at wages, the two AI measures are much more aligned: the more potentially exposed occupations are associated with higher average wage deciles for both AI measures - even though wages are higher for the most exposed according to the measure by Felten et al. than the one by Webb. Yet, relative wages remained broadly unchanged during this period. Considering digitalisation, wage deciles are relatively even across various scores on the software measure. Note that since wages are provided as deciles, changes over the 8 years between 2011 and 2019 are overall fairly small, as expected. Figures 2 and 3 visualise these employment and wage changes for occupations with low, medium or high technology scores.

Cross-country heterogeneity Some of these changes in employment shares and wage deciles may be masking heterogeneity across countries that fails to become evident in the pooled sample. Therefore, we provide an overview of all the countries and their respective employment shares and wage deciles in Appendix A (see Figures A3 - A12).

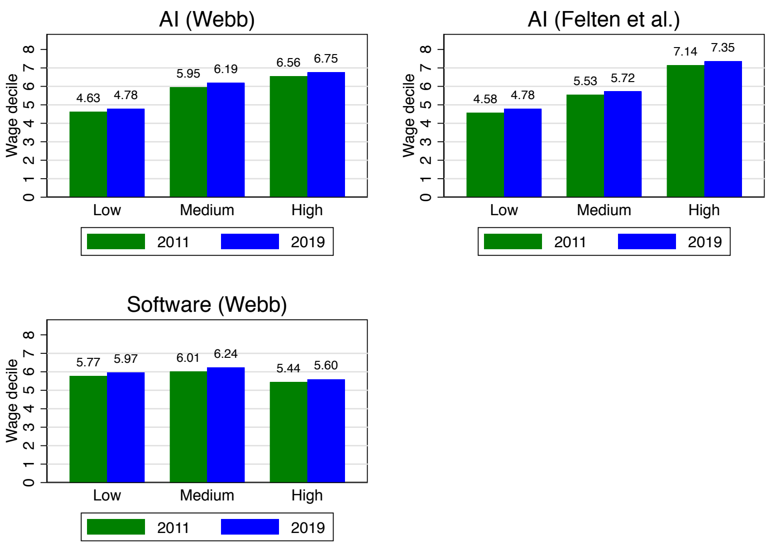
Overall, the aggregate descriptive patterns of changes in employment and relative wages by technology measures are not driven by specific countries. Results are in fact very heterogeneous across countries too. Figure 4 emphasises the heterogeneity across technology measures and countries for changes 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 measure. 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, as captured by Webb's software measure, seems to have increased them by more in the bottom 40 occupations.

Figure 2: 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 3: Wage deciles by technology measures



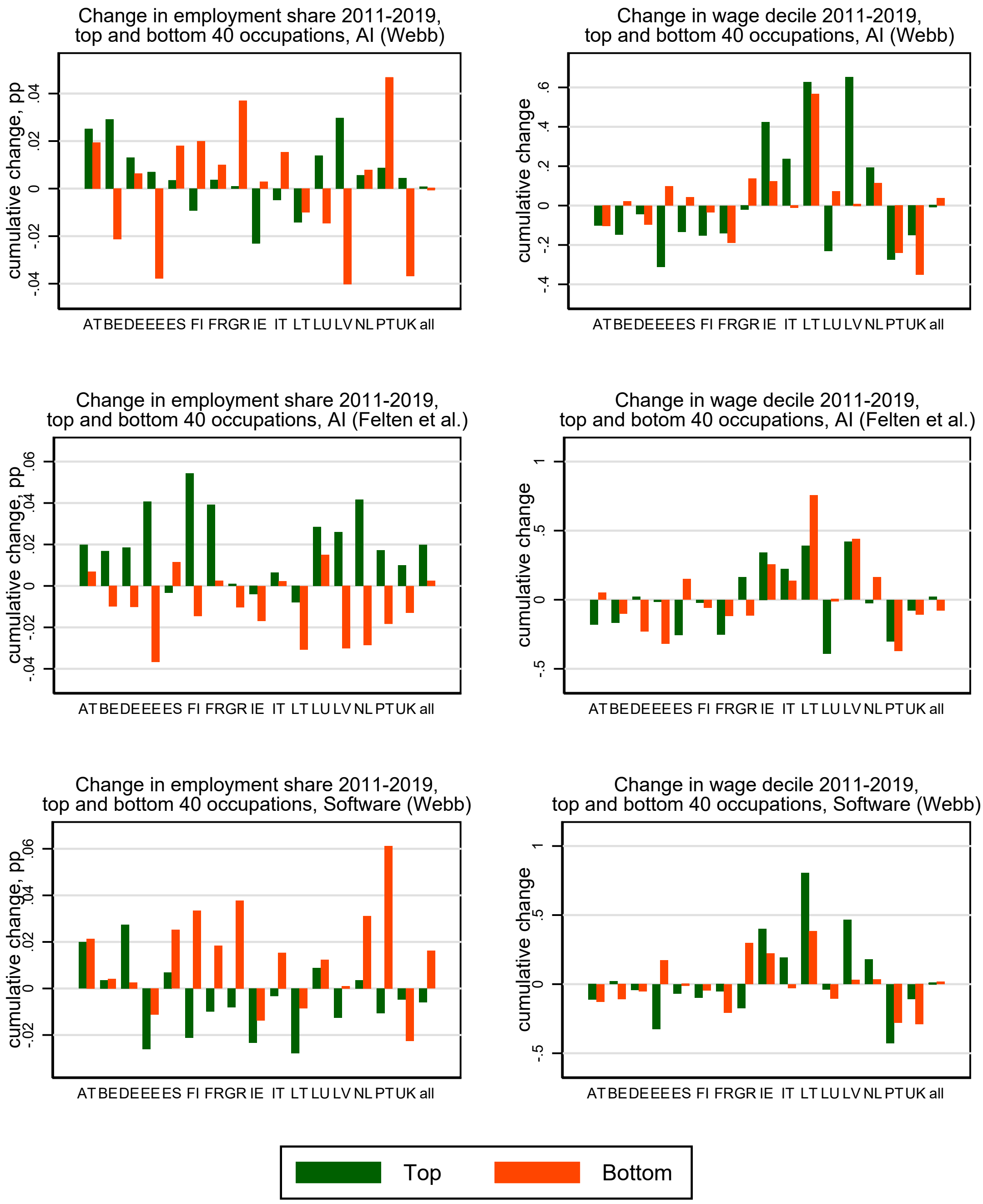
Notes: For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values were taken due to limited availability of values for 2019. Y-axis indicates average annual wage decile. Technology measure categories (low, medium, high) reflect terciles of the respective technology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

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.

To get a better understanding for which occupations might cause these differences across technologies, we now focus on only the top and bottom 5 occupations for each technology measure. This is shown in Appendix A (for employment shares see Table A4 and for wages see Table A5). When comparing employment shares and relative wages between 2011 and 2019 - and any respective changes during these years - the link between employment and wage changes appears weak: 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 with what we observe for the bottom five occupations. Here, regardless of the technology measure, the employment share increased in total between 0.04 and 0.07 percentage points. For wages, the 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 belief that to draw any meaningful conclusions, controlling for observables is important, as well as implementing employment-weights in our empirical analyses.

Figure 4: 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.

4 Empirical Analysis

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

$$y_{so,c} = \alpha_c + \alpha_s + \beta_c X_{so,c} + \epsilon_{so,c} \tag{7}$$

Our unit of analysis is a sector-occupation-country cell, occupations are categorised according to ISCO-2008 at the three-digit disaggregation level and sectors are grouped into six major aggregates, as mentioned in Section 3.[13] When focusing on employment, our dependent variable $y_{so,c}$ is the change in the employment share of sector-occupation *so* in country *c* from 2011 to 2019. This change in the employment share is measured as a percentage change relative to the midpoint of a cell's share of overall employment from 2011 to 2019, winsorised at the top and bottom 1%. 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 to deal with entry and exit of units of observation, in our case sector-occupation cells).[14] When examining the relationship of technology and relative wages, $y_{so,c}$ captures the change in the wage distribution position of sector-occupation *so* in country *c* also from 2011 to 2019.

$X_{so,c}$ are the measures of potential exposure of the sector-occupation-country 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. We transform the technology scores to be employment-weighted percentiles, so that we can interpret our results in terms of workers, using the employment in each cell in the initial year of the sample as weights . This transformation into percentiles also allows us to compare our results with other results in the

[13] We therefore focus the analysis on within-sector changes in the relative demand for occupations in each country. This helps to isolate changes in demand for occupations that are due to task-level substitution on the production side or specific to a country. See for example Webb (2020)

[14] See for example Davis et al. (1996) and Webb (2020).

literature (e.g., Webb (2020)). Thus, our $X_{so,c}$ takes values from 1 to 100, where 90 means that 10% of workers work in cells with a higher exposure to technology. Nevertheless, in some of the specifications that we estimate, we also use unweighted percentiles of the technology scores. In this case, a cell $X_{so,c}$ equalling 90 means that 10% of cells have a higher exposure to technology. α_c and α_s are country and sector fixed effects. Observations are weighted by cells' average labour supply; standard errors are two-way clustered by sector and country. 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 shares and relative wages) is interpreted as automation displacing employment. There could also be cases, where 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 reinstatement effect, where some tasks or jobs are destroyed, but new ones are created within the same occupation-sector cell.

The model presented previously in Section 2 illustrates how the relative sizes of productivity, displacement and reinstatement effects associated with technological changes can be rationalised. The statistical associations reported in this section just provide a first order 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.

4.1 Pooled Results

We start discussing results for the pooled sample of countries.[15]

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

[15]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).

indicator of exposure to AI used to proxy AI-enabled automation, as implied by the positive and significant coefficients in Table B1 in Appendix B. Table B1 show estimation results for various specifications of equation 7, including some in which the technology proxy is not employment weighted. Results are robust across specifications. The rest of the discussion in this section will refer to the simplest specification as in column 1 of Table B1 in Appendix B, which is also the first column of Table 3.

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 have so far been small.

When estimating equation 7 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 and Table B2). It could be found puzzling that relative wages do not increase in occupations more exposed to AI, while relative employment does increase in those occupations. However, there are some caveats regarding the interpretation of the wage results: First, our measure of relative wages is based in rankings, as the cross-country EU-LFS provides the monthly pay of workers in *deciles*, hence, does not fully account for quantitative changes.[16] Secondly, under collective bargaining, the most prevalent mechanism for wage determination in Europe, relative wages are more "rigid" as unions care more about wages in the bottom part of the wage distribution. With rigid relative wages employment shares would adjust more to changes in the occupational distribution of labour demand. Finally, there could be a supply-side explanation, if relative labour supply of the more demanded occupations increases. However, information on university enrolments by fields during the 2013-2019 period in the countries in our sample does not support the view that labour supply is responding to higher demand of the skills embodied in the so-called STEM disciplines, which are generally more potentially exposed to AI innovations.[17]

Our results stand in some contrast with findings for the US. For example, both Felten et al.

[16]When aggregating to occupation-sector country cells we measure wages by within country centiles of employment-weighted average wages for each sector-occupation cell in 2011.
[17]Data available upon request.

(2019) and Acemoglu et al. (2022) conclude that occupations more exposed to AI experience no visible impact on employment. However, Acemoglu et al. (2022) find that AI-exposed establishments reduced non-AI and overall hiring, implying that AI is substituting human labour in a subset of tasks, while new tasks are created.

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)
AIW	0.104***	0.212***	0.106**	0.015	-0.008	-0.028	0.125**
	(0.027)	(0.046)	(0.046)	(0.040)	(0.055)	(0.045)	(0.048)
Observations	6767	2160	1653	2954	2145	1979	2641
AIF	0.174***	0.219***	0.132**	0.144***	-0.088	-0.068	0.266***
	(0.034)	(0.067)	(0.051)	(0.042)	(0.092)	(0.087)	(0.073)
Observations	5766	1828	1369	2569	1809	1632	2323
Software	-0.025	0.107***	-0.083*	-0.117**	0.004	-0.032	0.044
	(0.025)	(0.033)	(0.044)	(0.053)	(0.042)	(0.047)	(0.050)
Observations	6767	2160	1653	2954	2145	1979	2641

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

To gain a better understanding of what is driving the positive relationship between employment and AI exposure, we explore the role of sectors and of particular groups of occupations, by using alternative samples in the estimations. Results of sequentially leaving one sector out of the estimation sample are shown in Table B3. Similarly, Table B5 presents the result of sequentially excluding those 3-digit ISCO-08 occupations that can be grouped in each ISCO-08 major group (1-digit code level groups). A remarkable result is that the occupation group *Professionals* (ISCO-08 major group 2) seem to be driving our results. This group consists of occupations whose main tasks require a high level of professional knowledge and experience in the fields of physical and life sciences, or social sciences and humanities. The fact that occupations that employ high-skilled labour are what could be called *AI-taker* occupations, is in line with a widespread concern that AI could foster inequality.

The fact that new technologies might induce changes in the relative shares of employment

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

	All (1)	Younger (2)	Core (3)	Older (4)	LowEduc (5)	MedEduc (6)	HighEduc (7)
(a) AI, Webb	0.001	0.012	0.007	-0.009	-0.014	0.009	0.034**
	(0.006)	(0.011)	(0.015)	(0.012)	(0.009)	(0.015)	(0.014)
Observations	5729	1772	1534	2423	1834	1648	2246
(b) AI, Felten	-0.013*	0.004	-0.022	-0.021**	-0.051**	0.027*	0.008
	(0.008)	(0.012)	(0.017)	(0.009)	(0.023)	(0.015)	(0.027)
Observations	4872	1506	1263	2103	1550	1343	1978
(c) Software	0.007	0.018*	0.015	-0.005	-0.010	-0.014	0.026**
	(0.007)	(0.010)	(0.015)	(0.016)	(0.008)	(0.015)	(0.012)
Observations	5729	1772	1534	2423	1834	1648	2246

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 initial year of the sample. 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.

along the skill distribution and thus impact within-occupation earnings inequality has been a long-standing concern. 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 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.

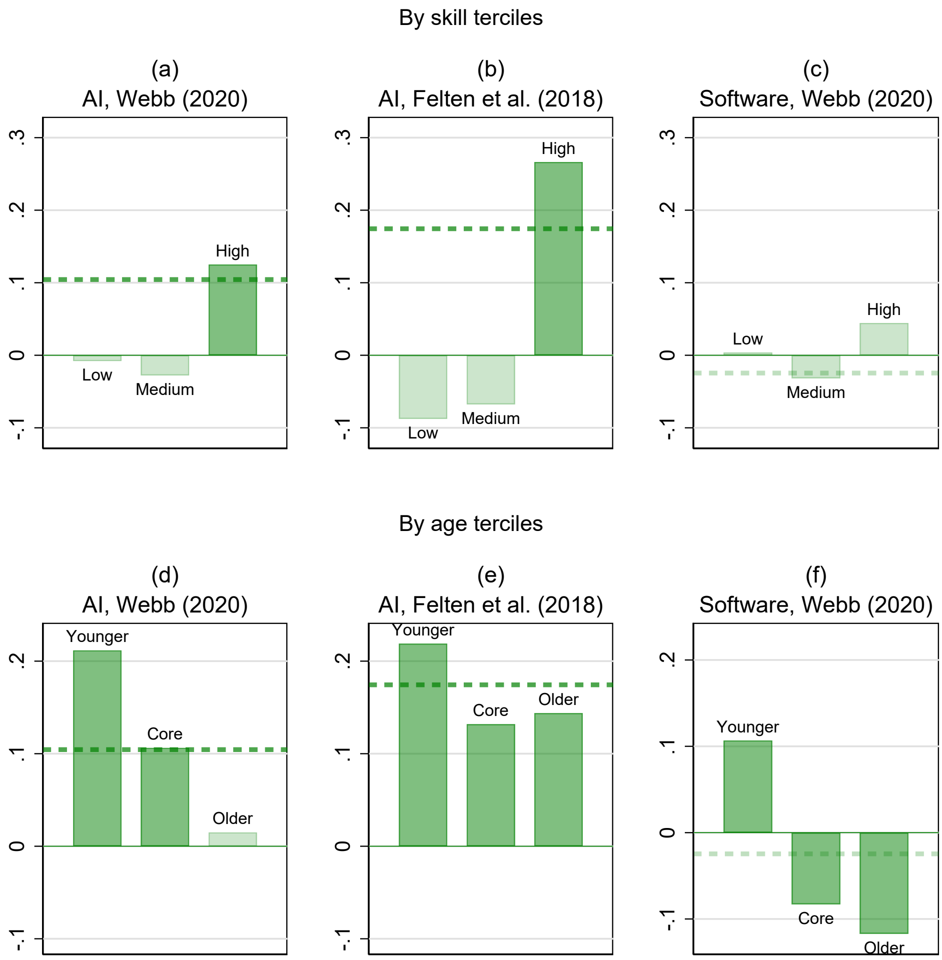
Plots (a) and (b) in Figure 5 display the estimated coefficients of the association between changes in employment and AI-enabled automation for the terciles of occupations that employ low, medium and high-skilled workers. The aggregate coefficient for all the skills is displayed by a red horizontal line, 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 5, 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 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 5 and Table 3). Regarding age, panel (f) in Figure 5, 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. Recall that we use software to compare the effects of an established technology with a new technology and to assess to which extent the two technologies may differently impact employment and wages. Our approach is not sufficient to test for labour market polarisation as that would require further analyses beyond the split of the sample into education terciles.

Figure 5: 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.

4.2 Results by Country

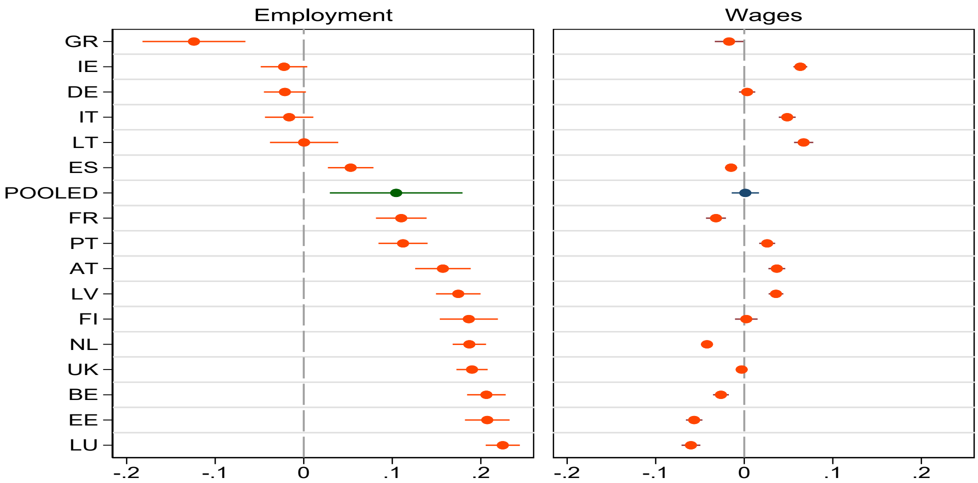
In this subsection we explore the impact of new technologies within countries. Our prior is that it will vary depending on each country's distribution of employment across sectors and occupations, which are differently exposed to the technologies.

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 6 and 7, 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.[18] 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 8 compares the estimates in a scatter plot using both measures of AI.

Regarding wages (see the right panel in Figures 6 and 7) 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.

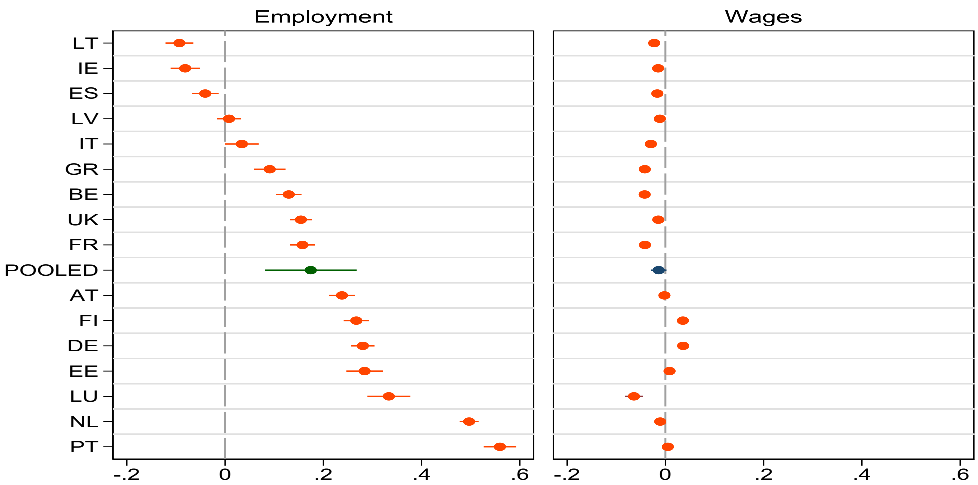
[18]For detailed regression results see tables in Appendix B.

Figure 6: Exposure to AI, Webb, and changes in employment shares and wage percentiles, by countries



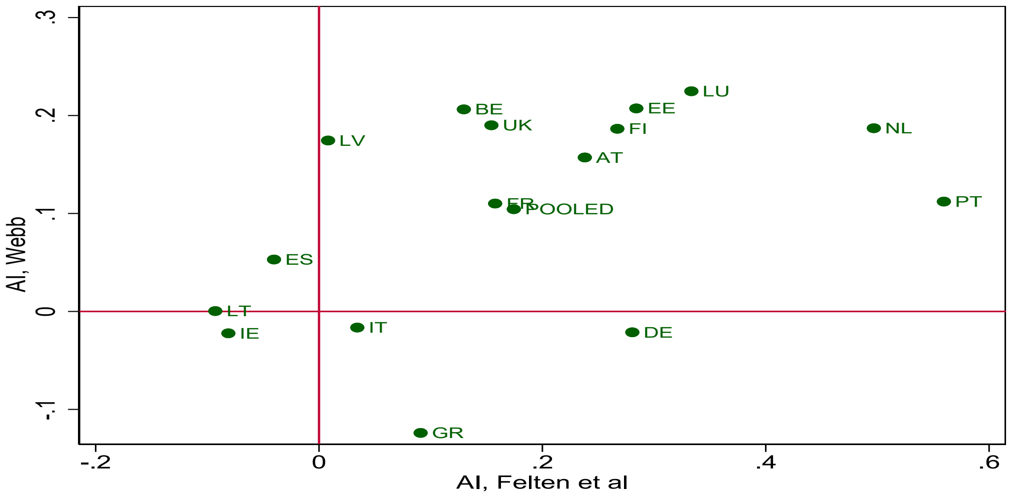
Notes: βc and β coefficients from employment shares and from relative wages regressions respectively in the same graph. See notes in tables B7 and B8.

Figure 7: 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 B9 and B10.

Figure 8: Exposure to AI, Webb and Felten et al., and changes in employment shares, by country



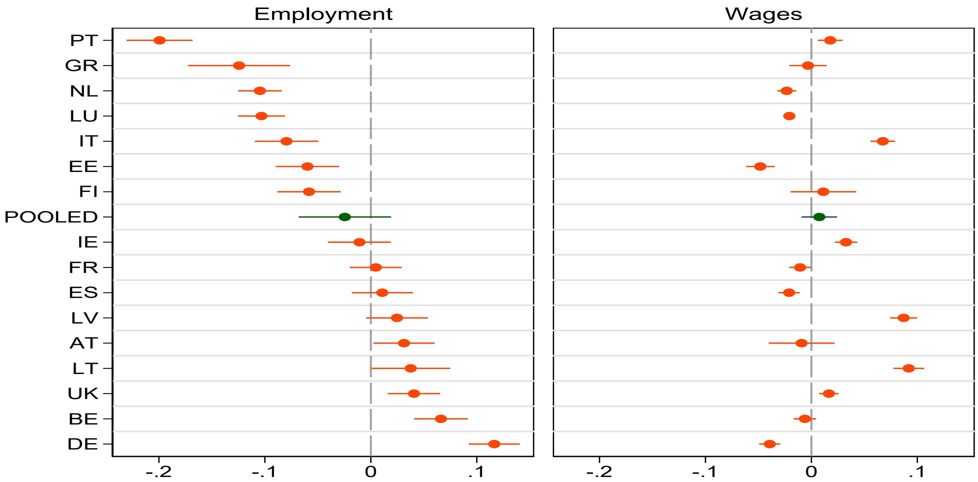
Notes: Scatter plot of regression coefficients measuring the effect of exposure to AI on changes in employment share. X-axis: regression coefficients using the AI proxy based on Felten et al. Y-axis: regression coefficients using the AI proxy based on Webb. For further details see notes to Figure 5.

Software Exposure to software is associated with declines in employment shares in various 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 9 and table B13 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 B13, which is in line with the so called Routinisation or labour market polarisation.

4.3 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 explain-

Figure 9: 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 B13 and B14.

ing 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 results 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.

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.

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
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.

5 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.

As for software, a technology that has already been around for several decades and that is of a different nature than AI, we do not find a statistically significant impact for occupations being exposed to this technology. This may partly be explained by the vast cross-country heterogeneity in results, as we still see software having a negative impact on middle-skilled jobs for a number of individual countries.

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. AI-enabled technologies continue to be developed and adopted and most of their impact on employment and wages are yet to be realised.

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Appendix A: Additional Descriptive Evidence

This appendix complements the descriptive evidence shown in Subsection 3.3.

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).[19] 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 2 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

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

scores appear to be linked to lower wage deciles (see Figure 3).

Some of the changes in employment shares and wage deciles that are discussed here may be 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 A3 - A12).

Figure 4 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	Top 5 occupations					Bottom 5 occupations				
	Rank	Occupation	Employment Share (%)			Rank	Occupation	Employment Share (%)		
			(2011)	(2019)	(Change)			(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

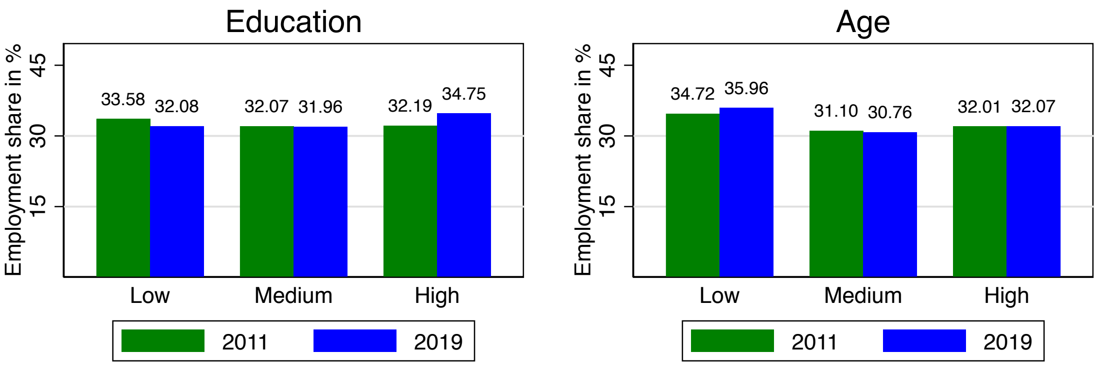
Notes: 3-digit top and bottom five occupations by technology measures (ISCO 2008 classification in brackets). Employment shares are displayed as percentages, changes in employment shares are given as percentage point differences.

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

Technology Measure	Top 5 occupations					Bottom 5 occupations				
	Rank	Occupation	Income Decile			Rank	Occupation	Income Decile		
			(2011)	(2019)	(Change)			(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

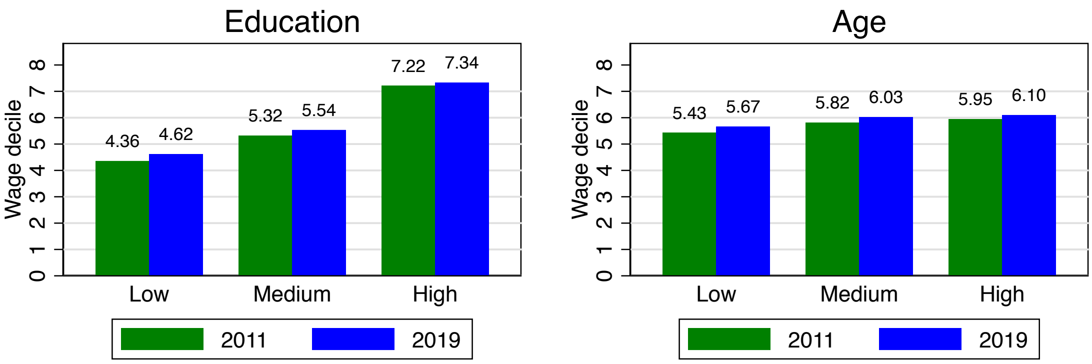
Notes: 3-digit top and bottom five occupations by technology measures (ISCO 2008 classification in brackets). Wage shown as average unweighted annual deciles, changes are differences in average deciles. For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values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

Figure A1: Employment shares by worker demographics



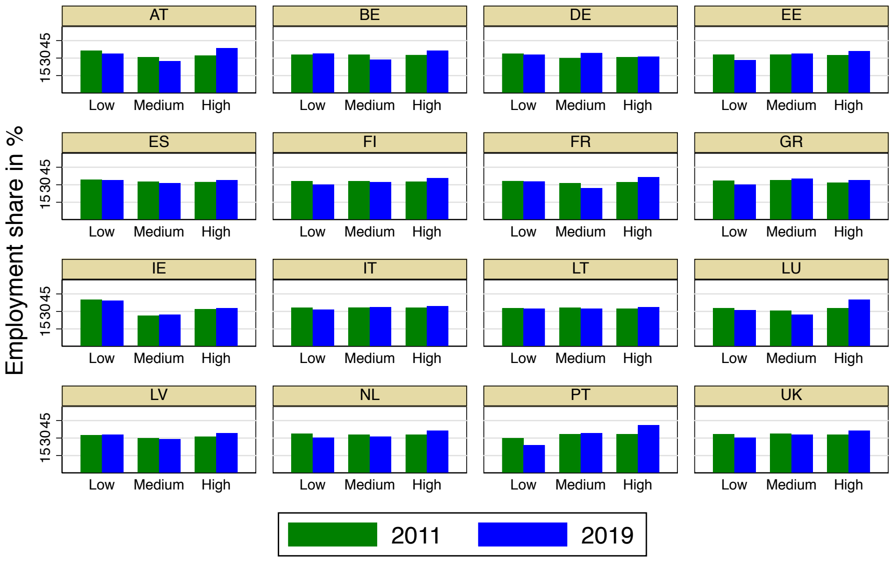
Notes: Y-axis indicates average annual employment shares. Education categories (low, medium, high) reflect terciles of a country's educational attainment distribution. Age categories (low, medium, high) reflect terciles of workers' age distribution in 2011.

Figure A2: Wage deciles by worker demographics



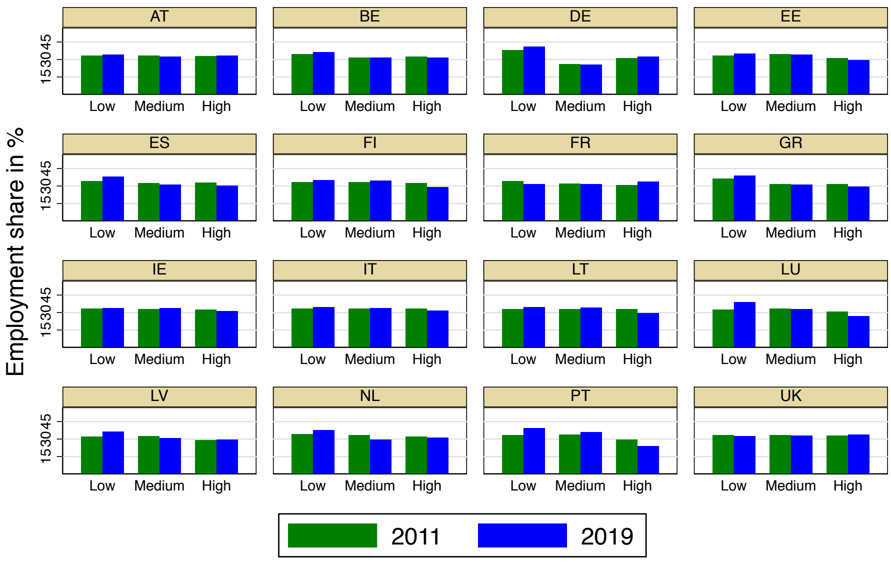
Notes: For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values were taken due to limited availability of values for 2019. Y-axis indicates average annual wage decile. Education categories (low, medium, high) reflect terciles of a country's educational attainment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

Figure A3: Employment shares by education across countries



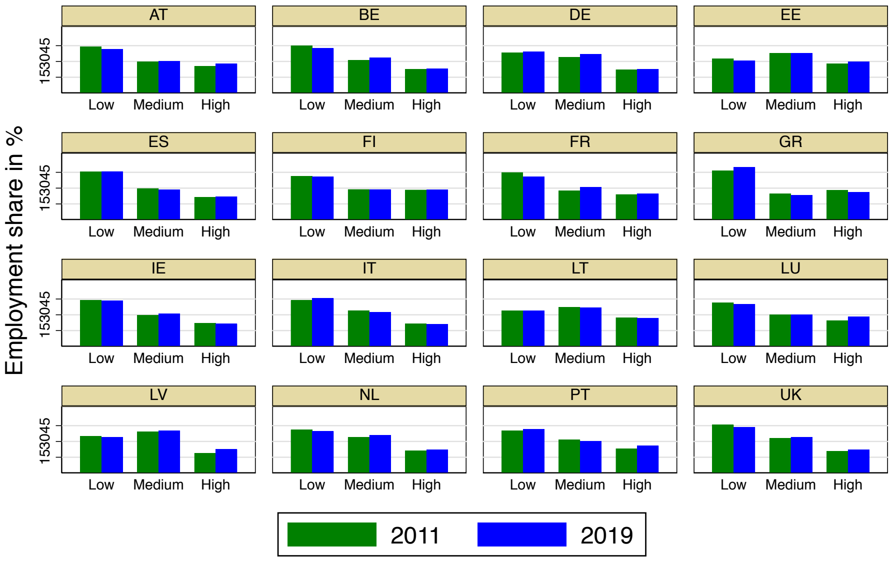
Notes: Y-axis indicates average annual employment shares. Education categories (low, medium, high) reflect terciles of a country's educational attainment distribution.

Figure A4: 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 A5: 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.

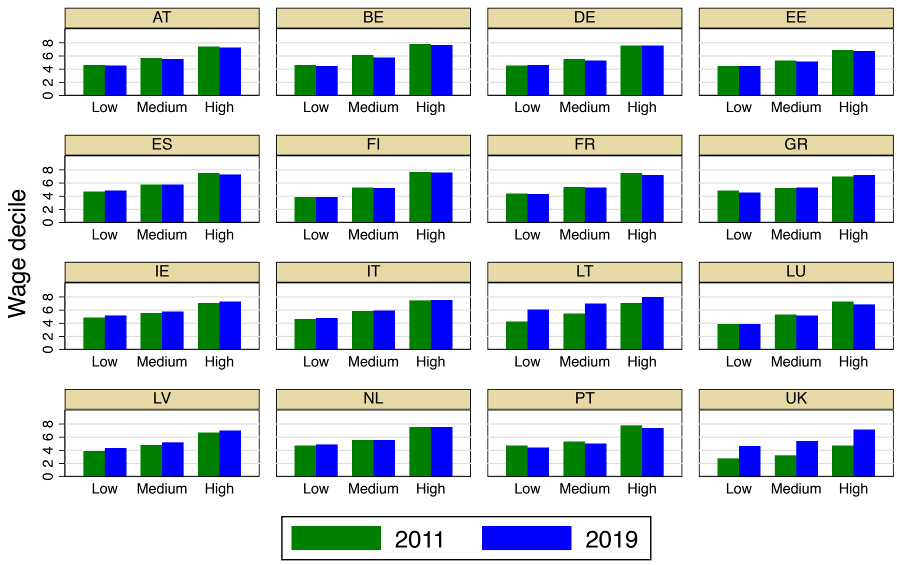
Figure A6: Employment shares by AI (Felten et al.) across countries

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 A7: Employment shares by software across countries

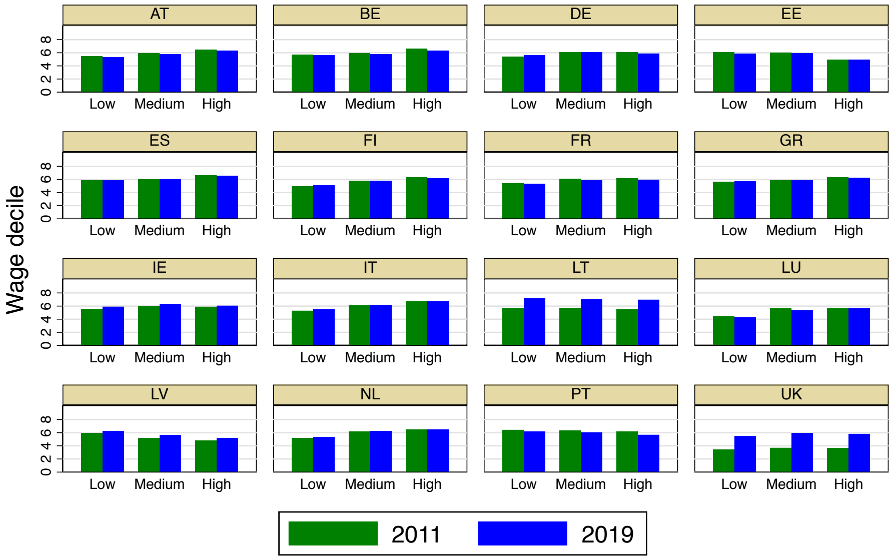
Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores based on the distribution of occupations in 2011.

Figure A8: Wage deciles by education across countries



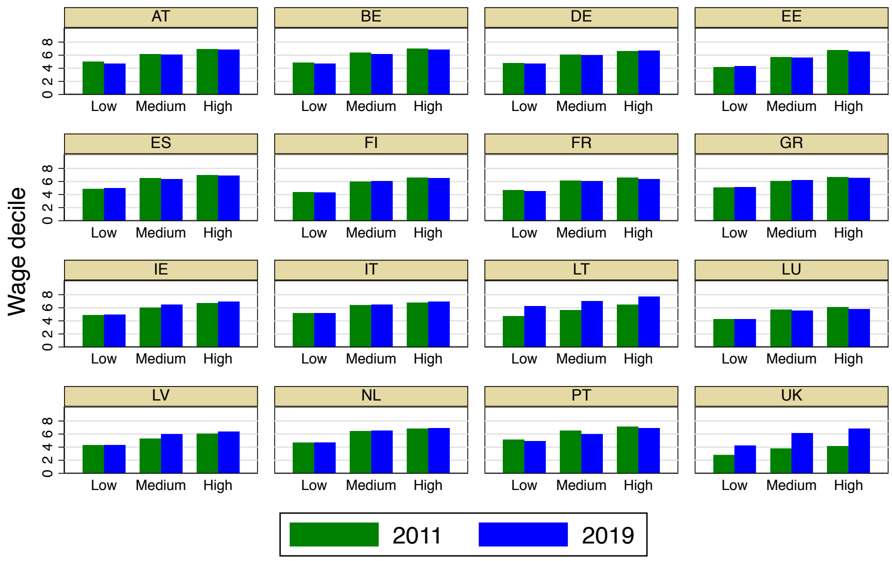
Notes: For AT and ES 2018 wage values were taken due to missing values for 2019. For FI 2017 wage values were taken due to limited availability of values for 2019. Y-axis indicates average annual unweighted wage decile. Education categories (low, medium, high) reflect terciles of a country's educational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

Figure A9: Wage deciles by age across countries



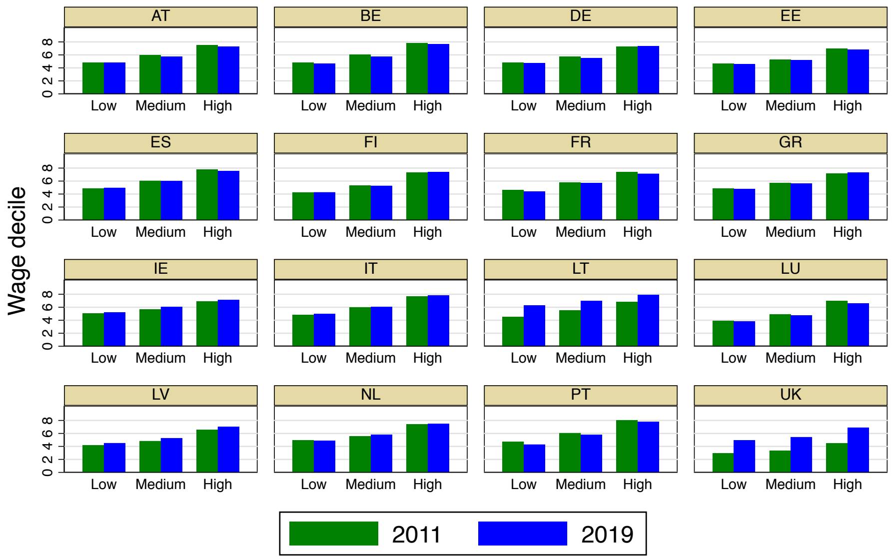
Notes: Values for the UK are excluded for data limitation reasons. 2018 wage values were taken for AT and ES due to missing values for 2019. Y-axis indicates unweighted average annual wage decile. Age categories (low, medium, high) reflect terciles of workers' age distribution in 2011.

Figure A10: Wage deciles by AI (Webb) across countries



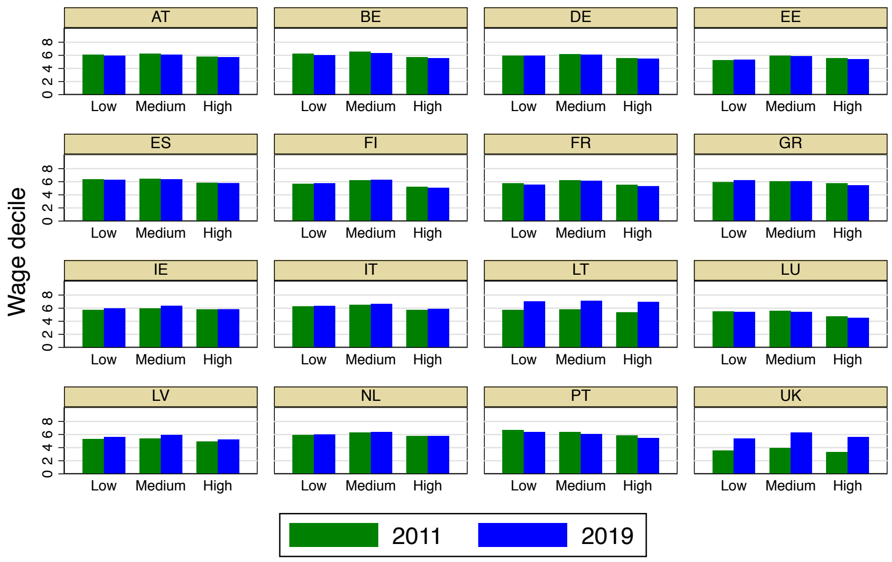
Notes: Values for the UK are excluded for data limitation reasons. 2018 wage values were taken for AT and ES due to missing values for 2019. Y-axis indicates unweighted average annual wage decile. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's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

Figure A11: 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 A12: 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.

Appendix B

This appendix complements the evidence shown in Section 4.

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

	(1)	(2)	(3)	(4)	(5)
AI, Webb	0.104***	0.111***			0.192***
	(0.027)	(0.027)			(0.037)
AI,Webb.Unweigthed			0.099***	0.106***	
			(0.029)	(0.029)	
Software Exp					-0.143***
					(0.036)
Observations	6767	6767	6767	6767	6767
AI, Felten	0.174***	0.174***			0.175***
	(0.034)	(0.034)			(0.036)
AI,Felten.Unweigthed			0.175***	0.176***	
			(0.034)	(0.034)	
Software Exp					0.015
					(0.031)
Observations	5766	5766	5766	5766	5750

Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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. AI variables in columns (1), (2) and (5) are 2011 employment weighted percentiles of AI scores, columns (3) and (4) show the results for unweighted pecentiles of AI scores. In columns (1) and (3) sector and country dummies are included. In column (2) and (4) sector*country dummies included. Columns (5) as (1) plus the Software exposure measure as in Webb (2019).

Table B2: Relative wage changes vs. exposure to AI. Pooled sample 2011-2019

	(1)	(2)	(3)	(4)	(5)
AI, Webb	0.001	0.001			-0.003
	(0.006)	(0.006)			(0.008)
AI,Webb.Unweighted			0.001	0.001	
			(0.006)	(0.006)	
Software Exp					0.008
					(0.008)
Observations	5729	5729	5733	5733	5729
AI, Felten	-0.013*	-0.011			-0.011
	(0.008)	(0.008)			(0.008)
AI,Felten.Unweighted			-0.013	-0.012	
			(0.008)	(0.008)	
Software Exp					0.003
					(0.007)
Observations	4872	4872	4875	4875	4866

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 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. AI variables in columns (1), (2) and (5) are 2011 employment weighted percentiles of AI scores, columns (3) and (4) show the results for unweighted pecentiles of AI scores. In columns (1) and (3) sector and country dummies are included. In column (2) and (4) sector*country dummies included. Columns (5) as (1) plus the Software exposure measure as in Webb (2019).

Table B3: Changes in employment vs. exposure to AI. 2011-2019. Sectors.

	(All)	(1)	(2)	(3)	(4)	(5)	(6)
AI, Webb	0.104***	0.112***	0.101***	0.090***	0.113***	0.092***	0.135***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.029)	(0.032)	(0.040)
Observations	6767	6106	5877	6133	5403	5257	5059
AI, Felten	0.174***	0.169***	0.162***	0.166***	0.184***	0.159***	0.233***
	(0.034)	(0.034)	(0.035)	(0.034)	(0.039)	(0.040)	(0.036)
Observations	5766	5189	4994	5247	4628	4476	4296

Notes: See notes for column (1) in Table B1. Column named (All) includes the whole sample. The rest of the columns exclude one sector. Column named (1) excludes agriculture; (2) excludes construction; (3) excludes financial services; (4) excludes services; (5) excludes manufacturing and (6) excludes public services.

Table B4: Changes in relative wages vs. exposure to AI. 2011-2019. Sectors.

	(All)	(1)	(2)	(3)	(4)	(5)	(6)
AI, Webb	0.001	0.002	-0.001	0.002	0.000	-0.000	0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.010)
Observations	5729	5323	5033	5258	4547	4367	4117
AI, Felten	-0.013*	-0.012	-0.012	-0.013	-0.008	-0.013	-0.029***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.011)
Observations	4872	4510	4273	4488	3894	3711	3484

Notes: See notes for column (1) in Table B2. Column named (All) includes the whole sample. The rest of the columns exclude one sector. Column named (1) excludes agriculture; (2) excludes construction; (3) excludes financial services; (4) excludes services; (5) excludes manufacturing; and (6) excludes public services.

Table B5: Change in employment vs exposure to AI. 2011-2019. Occupations

	(All)	(1)	(2)	(3)	(4	(5)	(6)	(7)	(8)	(9)
AI, Webb	0.104***	0.118***	0.011	0.116***	0.069**	0.117***	0.118***	0.114***	0.122***	0.120***
	(0.027)	(0.027)	(0.030)	(0.030)	(0.029)	(0.030)	(0.028)	(0.028)	(0.030)	(0.031)
Observations	6767	6113	5354	5621	6203	6101	6560	5877	6093	6214
AI, Felten	0.174***	0.195***	0.050	0.196***	0.170***	0.200***	0.169***	0.151***	0.174***	0.225***
	(0.034)	(0.035)	(0.042)	(0.034)	(0.034)	(0.033)	(0.034)	(0.037)	(0.034)	(0.041)
Observations	5766	5165	4559	4630	5579	5204	5557	4876	5302	5256

Notes: See notes for column (1) in Table B1. Column named (All) includes the whole sample. The rest of the columns exclude occupations in one of ISCO major groups. Column named (1) excludes managers; (2) excludes professional; (3) excludes technicians; (4) excludes clerical support workers; (5) services and sales workers ; (6) skill agriculture, forestry and fishing; (7) craft workers; (8) plant and machine operators (9) elementary occupations.

Table B6: Change in relative wages vs exposure to AI. 2011-2019. Occupations

	(All)	(1)	(2)	(3)	(4	(5)	(6)	(7)	(8)	(9)
AI, Webb	0.001	0.003	-0.001	-0.001	-0.000	0.005	0.002	0.001	0.002	0.006
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)
Observations	5729	5221	4533	4757	5224	5184	5581	4971	5145	5216
AI, Felten	-0.013*	-0.014*	-0.013	-0.013	-0.014*	-0.018*	-0.012	-0.011	-0.018**	-0.004
	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)	(0.008)	(0.010)
Observations	4872	4398	3857	3902	4711	4404	4723	4114	4464	4403

Notes: See notes for column (1) in Table B2. Column named (All) includes the whole sample. The rest of the columns exclude occupations in one of the ISCO major groups. Column named (1) excludes managers; (2) excludes professional; (3) excludes technicians; (4) excludes clerical support workers; (5) services and sales workers ; (6) skill agriculture, forestry and fishing; (7) craft workers; (8) plant and machine operators (9) elementary occupations.

Table B7: 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***							
	(0.027)							
AI_W x AT		0.156***	0.332***	0.103	0.015	-0.070	0.167	0.041
		(0.041)	(0.031)	(0.124)	(0.074)	(0.113)	(0.108)	(0.083)
AI_W x BE		0.205***	0.329***	0.226	0.091**	-0.060	0.069	0.318
		(0.057)	(0.071)	(0.225)	(0.041)	(0.096)	(0.147)	(0.209)
AI_W x DE		-0.022	0.292***	-0.112	-0.163	0.409*	-0.122	-0.341***
		(0.110)	(0.090)	(0.193)	(0.139)	(0.245)	(0.175)	(0.106)
AI_W x EE		0.206**	0.516***	0.310**	-0.177*	0.052	0.061	0.238
		(0.087)	(0.083)	(0.138)	(0.103)	(0.115)	(0.156)	(0.157)
AI_W x ES		0.052	0.020	0.152**	0.081	-0.014	-0.261***	0.263***
		(0.055)	(0.076)	(0.070)	(0.054)	(0.046)	(0.088)	(0.034)
AI_W x FI		0.185***	0.261***	0.257***	0.089	-0.012	0.348***	-0.063
		(0.048)	(0.073)	(0.054)	(0.173)	(0.144)	(0.057)	(0.095)
AI_W x FR		0.109***	0.117	0.171	0.104	0.163***	-0.172	0.089
		(0.038)	(0.168)	(0.147)	(0.075)	(0.044)	(0.171)	(0.128)
AI_W x GR		-0.125	-0.038	-0.249	0.040	-0.134	-0.396***	-0.064
		(0.104)	(0.066)	(0.154)	(0.193)	(0.240)	(0.068)	(0.165)
AI_W x IE		-0.023	0.040	0.018	-0.087*	-0.054	-0.110	-0.114
		(0.053)	(0.154)	(0.093)	(0.051)	(0.076)	(0.101)	(0.080)
AI_W x IT		-0.018	0.080	-0.163	0.020	-0.074	-0.061	-0.087
		(0.076)	(0.061)	(0.136)	(0.074)	(0.139)	(0.095)	(0.083)
AI_W x LT		-0.001	-0.100	0.316*	-0.174	-0.481***	-0.002	0.408***
		(0.065)	(0.110)	(0.171)	(0.228)	(0.154)	(0.130)	(0.087)
AI_W x LU		0.224***	0.242***	0.418	-0.027	-0.092	-0.136	0.523**
		(0.074)	(0.056)	(0.253)	(0.147)	(0.150)	(0.100)	(0.246)
AI_W x LV		0.174*	0.313***	0.089	0.153	0.019	0.077	0.191
		(0.090)	(0.117)	(0.169)	(0.123)	(0.219)	(0.102)	(0.142)
AI_W x NL		0.186**	0.204*	0.162	0.190	-0.078	0.210	0.010
		(0.081)	(0.117)	(0.172)	(0.171)	(0.128)	(0.159)	(0.051)
AI_W x PT		0.111	0.365***	0.048	-0.190	0.193	-0.307***	0.347***
		(0.079)	(0.046)	(0.096)	(0.139)	(0.158)	(0.104)	(0.056)
AI_W x UK			0.279***	-0.013	0.263***	0.102	0.055	0.018
			(0.055)	(0.051)	(0.047)	(0.064)	(0.043)	(0.062)
Observations	6767	6767	2160	1653	2954	2145	1979	2641

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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: ARTIFICIAL INTELLIGENCE. COUNTRIES. 2011-19. Wage changes vs. exposure to AI, Webb (AI_W)

			Younger	Core	Older	LowSkill	MedSkill	HighSkill
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI, Webb	0.001							
	(0.006)							
AI_W x AT		0.037	0.012	0.115***	0.007	0.019	0.036	0.113***
		(0.022)	(0.028)	(0.036)	(0.022)	(0.016)	(0.060)	(0.013)
AI_W x BE		-0.026	-0.001	0.012	-0.073***	-0.025	-0.040	-0.002
		(0.016)	(0.020)	(0.051)	(0.018)	(0.017)	(0.042)	(0.037)
AI_W x DE		0.003	0.034**	-0.052**	0.019	0.001	-0.003	0.032
		(0.011)	(0.016)	(0.021)	(0.017)	(0.020)	(0.054)	(0.037)
AI_W x EE		-0.057**	0.053***	-0.119***	-0.131***	-0.049*	-0.061	-0.047
		(0.026)	(0.020)	(0.043)	(0.029)	(0.029)	(0.039)	(0.075)
AI_W x ES		-0.015	-0.006	-0.002	-0.028	-0.004	-0.038***	-0.003
		(0.014)	(0.006)	(0.016)	(0.023)	(0.022)	(0.011)	(0.009)
AI_W x FI		0.002	-0.016	0.072	-0.027	-0.047	0.035	0.046***
		(0.031)	(0.021)	(0.064)	(0.023)	(0.032)	(0.052)	(0.013)
AI_W x FR		-0.032**	-0.057	0.028	-0.056**	-0.013	-0.058**	0.056*
		(0.013)	(0.042)	(0.017)	(0.024)	(0.012)	(0.025)	(0.030)
AI_W x GR		-0.017**	0.056***	-0.134**	0.017	-0.099***	0.027	-0.063***
		(0.008)	(0.017)	(0.066)	(0.083)	(0.025)	(0.022)	(0.016)
AI_W x IE		0.063*	0.030***	0.084*	0.074	0.092	0.041	0.085**
		(0.034)	(0.007)	(0.046)	(0.079)	(0.084)	(0.025)	(0.037)
AI_W x IT		0.049***	0.047***	0.080***	0.056***	0.008	0.055***	0.077***
		(0.010)	(0.008)	(0.014)	(0.016)	(0.016)	(0.020)	(0.028)
AI_W x LT		0.067***	0.106***	0.008	0.098***	0.008	0.108***	0.129***
		(0.022)	(0.022)	(0.045)	(0.025)	(0.018)	(0.039)	(0.034)
AI_W x LU		-0.060*	-0.044	-0.082*	-0.052	-0.044**	-0.063	-0.091
		(0.034)	(0.032)	(0.042)	(0.050)	(0.020)	(0.070)	(0.075)
AI_W x LV		0.036	0.090***	0.067	-0.019	-0.022	0.076*	0.154
		(0.030)	(0.025)	(0.096)	(0.059)	(0.049)	(0.038)	(0.136)
AI_W x NL		-0.042***	-0.065***	-0.023	-0.008	-0.073***	-0.040*	-0.069*
		(0.014)	(0.015)	(0.026)	(0.020)	(0.016)	(0.024)	(0.039)
AI_W x PT		0.026*	-0.028*	0.056**	0.062**	0.005	0.017	0.044*
		(0.014)	(0.016)	(0.028)	(0.031)	(0.030)	(0.040)	(0.023)
AI_W x UK		-0.003	0.025	0.006	-0.015	-0.027	0.031	0.053***
		(0.018)	(0.018)	(0.021)	(0.020)	(0.040)	(0.026)	(0.019)
Observations	5729	5729	1772	1534	2423	1834	1648	2246

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 B9: ARTIFICIAL INTELLIGENCE. COUNTRIES. 2011-19. Change in employment vs. exposure to AI, Felten (AI_F)

			Younger	More	Older	LowSkill	MedSkill	HighSkill
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI, Felten	0.174***							
	(0.035)							
AI_F x AT		0.238***	0.383***	0.143**	0.163*	-0.071	-0.048	0.504***
		(0.031)	(0.098)	(0.063)	(0.095)	(0.183)	(0.159)	(0.085)
AI_F x BE		0.130***	0.187***	-0.150**	0.326**	-0.118	-0.007	0.759***
		(0.042)	(0.041)	(0.063)	(0.134)	(0.333)	(0.391)	(0.144)
AI_F x DE		0.281***	0.385***	0.444***	0.113**	0.689*	0.623***	0.303**
		(0.069)	(0.129)	(0.129)	(0.048)	(0.414)	(0.126)	(0.116)
AI_F x EE		0.284***	0.531***	0.155	-0.024	0.346**	-0.047	0.250
		(0.093)	(0.104)	(0.120)	(0.170)	(0.171)	(0.129)	(0.297)
AI_F x ES		-0.040	-0.021	-0.244*	0.084***	-0.174	-0.112	-0.285***
		(0.072)	(0.080)	(0.123)	(0.032)	(0.115)	(0.131)	(0.095)
AI_F x FI		0.267***	0.317***	0.263	0.260	-0.318	0.154	0.243
		(0.087)	(0.079)	(0.160)	(0.284)	(0.290)	(0.180)	(0.187)
AI_F x FR		0.158	0.074	0.231	0.250***	0.176	-0.242	0.121
		(0.139)	(0.334)	(0.247)	(0.049)	(0.370)	(0.430)	(0.322)
AI_F x GR		0.091	0.006	0.172	0.034	0.802*	-0.832***	-0.142
		(0.193)	(0.151)	(0.227)	(0.244)	(0.456)	(0.084)	(0.097)
AI_F x IE		-0.081	-0.106	-0.032	-0.148	-0.820***	-0.321	0.148
		(0.105)	(0.143)	(0.092)	(0.238)	(0.219)	(0.267)	(0.204)
AI_F x IT		0.034	-0.016	0.112	-0.002	0.196	-0.472***	0.065
		(0.108)	(0.167)	(0.126)	(0.147)	(0.284)	(0.104)	(0.114)
AI_F x LT		-0.093	-0.187***	-0.223	0.110	-0.807***	-0.250	0.307
		(0.074)	(0.052)	(0.146)	(0.210)	(0.245)	(0.194)	(0.218)
AI_F x LU		0.333***	0.544***	0.251	-0.050	-0.467	0.526**	0.836***
		(0.080)	(0.185)	(0.273)	(0.132)	(0.808)	(0.227)	(0.197)
AI_F x LV		0.008	-0.191	0.239	-0.032	-0.499	-0.256***	0.306*
		(0.103)	(0.244)	(0.190)	(0.134)	(0.475)	(0.088)	(0.161)
AI_F x NL		0.497***	0.498***	0.573***	0.435***	-0.223**	0.665***	0.929***
		(0.041)	(0.050)	(0.145)	(0.154)	(0.111)	(0.148)	(0.131)
AI_F x PT		0.559***	0.565***	0.433***	0.551***	0.408**	-0.211***	0.008
		(0.087)	(0.083)	(0.084)	(0.198)	(0.187)	(0.071)	(0.164)
AI_F x UK		0.154***	0.301***	0.045	0.105***	-0.264**	-0.220**	0.014
		(0.030)	(0.067)	(0.051)	(0.038)	(0.101)	(0.094)	(0.089)
Observations	5750	5766	1828	1369	2569	1809	1632	2323

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 B10: ARTIFICIAL INTELLIGENCE. COUNTRIES. 2011-19. Wage changes vs. exposure to AI, Felten (AI_F)

			Younger	Core	Older	LowSkill	MedSkill	HighSkill
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI, Felten	-0.013*							
	(0.008)							
AI_F x AT		-0.003	-0.022**	0.017	0.009	0.020	0.007	0.044
		(0.015)	(0.011)	(0.028)	(0.023)	(0.028)	(0.031)	(0.029)
AI_F x BE		-0.042	-0.029	-0.082***	-0.025	-0.009	-0.150**	-0.025**
		(0.029)	(0.030)	(0.024)	(0.024)	(0.073)	(0.071)	(0.010)
AI_F x DE		0.036**	0.058	0.022	0.036***	0.020	0.028	-0.013
		(0.017)	(0.039)	(0.025)	(0.010)	(0.097)	(0.029)	(0.062)
AI_F x EE		0.008	0.059***	-0.045	0.003	-0.095	-0.004	-0.149***
		(0.018)	(0.022)	(0.036)	(0.027)	(0.084)	(0.046)	(0.042)
AI_F x ES		-0.016	-0.061*	0.005	0.000	-0.066	-0.098***	0.022***
		(0.014)	(0.032)	(0.025)	(0.014)	(0.044)	(0.021)	(0.005)
AI_F x FI		0.037	0.008	0.064	0.036	0.041	0.138***	0.067*
		(0.027)	(0.012)	(0.045)	(0.042)	(0.101)	(0.031)	(0.039)
AI_F x FR		-0.041	-0.033**	-0.043	-0.026**	0.118***	0.030	-0.068
		(0.028)	(0.013)	(0.090)	(0.010)	(0.037)	(0.030)	(0.082)
AI_F x GR		-0.042**	0.073**	-0.084	-0.104	-0.435***	0.020	-0.063
		(0.018)	(0.034)	(0.053)	(0.069)	(0.060)	(0.029)	(0.069)
AI_F x IE		-0.015	0.049**	0.006	-0.099*	-0.084*	0.096	0.145*
		(0.038)	(0.019)	(0.040)	(0.059)	(0.044)	(0.079)	(0.081)
AI_F x IT		-0.029	-0.056*	-0.018	-0.004	-0.027	0.056**	0.005
		(0.020)	(0.030)	(0.018)	(0.016)	(0.031)	(0.023)	(0.041)
AI_F x LT		-0.023	-0.027	-0.046	0.001	-0.140**	0.053	0.256***
		(0.042)	(0.054)	(0.070)	(0.021)	(0.064)	(0.034)	(0.075)
AI_F x LU		-0.064	-0.002	-0.039	-0.185***	0.058	-0.083	-0.232***
		(0.048)	(0.036)	(0.066)	(0.042)	(0.039)	(0.115)	(0.071)
AI_F x LV		-0.011	0.081	-0.083	-0.071**	-0.261***	0.157***	0.341***
		(0.059)	(0.070)	(0.060)	(0.029)	(0.047)	(0.021)	(0.065)
AI_F x NL		-0.010	-0.019	-0.013	0.010	-0.053*	0.042***	-0.314***
		(0.025)	(0.037)	(0.043)	(0.006)	(0.027)	(0.012)	(0.063)
AI_F x PT		0.005	-0.024	0.028	0.030*	-0.038	0.101**	0.146***
		(0.016)	(0.028)	(0.028)	(0.017)	(0.058)	(0.040)	(0.031)
AI_F x UK		-0.014	-0.003	-0.008	-0.026	0.013	-0.024	0.105***
		(0.010)	(0.022)	(0.016)	(0.021)	(0.034)	(0.024)	(0.020)
Observations	4872	4872	1506	1263	2103	1550	1343	1978

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 B11: Relative change in employment vs. exposure to software, Webb. Pooled sample 2011-2019

	(1)	(2)	(3)	(4)
Software Exp	-0.025	-0.024		
	(0.025)	(0.025)		
Softw,Webb.Unweigthed			-0.026	-0.025
			(0.024)	(0.024)
Observations	6767	6767	6767	6767

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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. Software in columns (1) and (2) is 2011 employment weighted percentiles of Software scores, columns (3) and (4) show the results for unweighted pecentiles of sftware scores. In columns (1) and (3) sector and country dummies are included. In column (2) and (4) sector*country dummies included.

Table B12: Relative wage changes vs. exposure to software, Webb. Pooled sample 2011-2019

	(1)	(2)	(3)	(4)
Software Exp	0.007	0.006		
	(0.007)	(0.006)		
Sotfw,Webb.Unweighted			0.006	0.004
			(0.007)	(0.007)
Observations	5729	5729	5733	5733

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 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. oftware in columns (1) and (2) is 2011 employment weighted percentiles of Software scores, columns (3) and (4) show the results for unweighted pecentiles of sftware scores. In columns (1) and (3) sector and country dummies are included. In column (2) and (4) sector*country dummies included.

Table B13: 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							
	(0.025)							
Software x AT		0.031	0.192***	-0.021	-0.120***	-0.003	0.120	0.003
		(0.056)	(0.023)	(0.100)	(0.041)	(0.129)	(0.093)	(0.047)
Software x BE		0.066	0.212***	0.145**	-0.161*	-0.079	0.013	-0.020
		(0.049)	(0.065)	(0.056)	(0.089)	(0.052)	(0.191)	(0.094)
Software x DE		0.117	0.283***	-0.077	0.071	0.244***	0.276*	-0.110
		(0.086)	(0.063)	(0.079)	(0.145)	(0.064)	(0.143)	(0.071)
Software x EE		-0.060	0.168	-0.148**	-0.136	-0.082	0.089	0.396
		(0.113)	(0.180)	(0.071)	(0.140)	(0.147)	(0.125)	(0.356)
Software x ES		0.011	-0.033	0.278***	-0.055	-0.028	-0.203**	0.170***
		(0.085)	(0.094)	(0.096)	(0.079)	(0.123)	(0.079)	(0.037)
Software x FI		-0.058	0.133***	-0.189	-0.248**	-0.087	0.175***	-0.086
		(0.060)	(0.045)	(0.143)	(0.096)	(0.099)	(0.044)	(0.138)
Software x FR		0.005	0.109	-0.085	-0.015	0.236	-0.182	-0.091
		(0.126)	(0.073)	(0.337)	(0.194)	(0.204)	(0.143)	(0.306)
Software x GR		-0.124	-0.122	-0.365***	0.233*	-0.037	-0.204***	-0.036
		(0.090)	(0.112)	(0.106)	(0.133)	(0.318)	(0.028)	(0.153)
Software x IE		-0.011	0.184*	-0.107	-0.163	0.041	-0.051	-0.091
		(0.100)	(0.101)	(0.131)	(0.141)	(0.091)	(0.162)	(0.095)
Software x IT		-0.080	0.079	-0.359***	-0.122	0.087	-0.188**	-0.187***
		(0.068)	(0.070)	(0.106)	(0.149)	(0.120)	(0.077)	(0.052)
Software x LT		0.038	0.122	0.212	-0.267	-0.361*	0.049	0.256**
		(0.088)	(0.106)	(0.158)	(0.302)	(0.198)	(0.183)	(0.109)
Software x LU		-0.103	-0.098	0.016	-0.142	-0.076	-0.284***	0.275
		(0.085)	(0.085)	(0.129)	(0.210)	(0.083)	(0.080)	(0.249)
Software x LV		0.025	0.359	0.017	-0.187*	-0.295*	0.133	0.082
		(0.071)	(0.220)	(0.113)	(0.103)	(0.154)	(0.174)	(0.131)
Software x NL		-0.105**	0.053	-0.322***	-0.143	0.017	0.018	-0.073
		(0.045)	(0.071)	(0.082)	(0.116)	(0.066)	(0.114)	(0.065)
Software x PT		-0.199	0.006	-0.251*	-0.544***	0.229	-0.223**	0.202*
		(0.123)	(0.070)	(0.127)	(0.176)	(0.170)	(0.109)	(0.118)
Software x UK		0.041	0.101**	-0.158***	0.114*	0.101*	0.114	0.085
		(0.037)	(0.045)	(0.058)	(0.062)	(0.053)	(0.083)	(0.063)
Observations	6767	6767	2160	1653	2954	2145	1979	2641

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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 B14: 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	0.007							
	(0.007)							
Software x AT		0.010	0.006	0.043***	-0.015	-0.007	-0.022	0.068***
		(0.014)	(0.023)	(0.016)	(0.033)	(0.026)	(0.023)	(0.010)
Software x BE		-0.006	0.010	0.057	-0.079**	-0.034	-0.041	0.003
		(0.029)	(0.015)	(0.047)	(0.035)	(0.023)	(0.053)	(0.047)
Software x DE		-0.039**	-0.001	-0.077***	-0.057	-0.071***	0.005	0.007
		(0.020)	(0.023)	(0.022)	(0.040)	(0.027)	(0.052)	(0.032)
Software x EE		-0.048*	0.010	-0.037	-0.125***	0.013	-0.108***	0.023
		(0.027)	(0.011)	(0.062)	(0.046)	(0.025)	(0.036)	(0.103)
Software x ES		-0.021**	0.011	-0.048*	-0.038	-0.013	-0.065***	-0.014
		(0.009)	(0.022)	(0.027)	(0.030)	(0.014)	(0.015)	(0.010)
Software x FI		-0.009	0.001	0.017	-0.037	0.006	-0.059	0.015
		(0.019)	(0.011)	(0.059)	(0.026)	(0.023)	(0.038)	(0.013)
Software x FR		-0.011	-0.042**	0.047*	-0.027	-0.021*	-0.076**	0.039***
		(0.015)	(0.019)	(0.027)	(0.032)	(0.012)	(0.029)	(0.009)
Software x GR		-0.003	0.062***	-0.097***	-0.002	-0.103*	0.019	-0.080**
		(0.014)	(0.018)	(0.029)	(0.046)	(0.059)	(0.023)	(0.034)
Software x IE		0.033	0.002	0.039*	0.055	0.043	-0.026	0.021*
		(0.038)	(0.014)	(0.022)	(0.107)	(0.057)	(0.036)	(0.011)
Software x IT		0.067***	0.072***	0.102***	0.053**	0.014	0.026	0.102***
		(0.021)	(0.008)	(0.017)	(0.024)	(0.013)	(0.025)	(0.013)
Software x LT		0.092*	0.140***	0.031	0.145***	-0.002	0.079**	0.148**
		(0.049)	(0.016)	(0.086)	(0.045)	(0.030)	(0.034)	(0.067)
Software x LU		-0.021	-0.014	-0.056***	0.040	-0.046***	0.015	-0.035
		(0.018)	(0.031)	(0.019)	(0.042)	(0.013)	(0.086)	(0.069)
Software x LV		0.087	0.119***	0.154*	0.084	0.072	0.035	0.184*
		(0.057)	(0.022)	(0.086)	(0.066)	(0.068)	(0.030)	(0.094)
Software x NL		-0.023***	-0.032	-0.016	0.005	-0.025	-0.046	0.004
		(0.008)	(0.024)	(0.045)	(0.027)	(0.020)	(0.038)	(0.016)
Software x PT		0.018	-0.007	0.045	0.010	0.041	-0.012	-0.000
		(0.014)	(0.013)	(0.035)	(0.034)	(0.037)	(0.020)	(0.033)
Software x UK		0.016	0.019	0.044	0.012	-0.020	0.062*	0.014
		(0.017)	(0.012)	(0.031)	(0.029)	(0.024)	(0.036)	(0.013)
Observations	5729	5729	1772	1534	2423	1834	1648	2246

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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