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ABSTRACT

Does Robotization Affect Job Quality? Evidence from European Regional Labour Markets*

Whereas there are recent papers on the effect of robot adoption on employment and wages, there is no evidence on how robots affect non-monetary working conditions. We explore the impact of robot adoption on several domains of non-monetary working conditions in Europe over the period 1995–2005 combining information from the World Robotics Survey and the European Working Conditions Survey. In order to deal with the possible endogeneity of robot deployment, we employ an instrumental variables strategy, using the robot exposure by sector in other developed countries as an instrument. Our results indicate that robotization has a negative impact on the quality of work in the dimension of work intensity and no relevant impact on the domains of physical environment or skills and discretion.

JEL Classification: J24, J81, O33

Keywords: robotization, working conditions, job quality, Europe, regional labour markets

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1. Introduction

Automation means a major force in today's labour markets, contributing to rising living standards (Atack et al., 2019; Autor, 2015; Autor & Salomons, 2018), but also being considered a relevant source of anxiety for citizens: 75% of Europeans see technological progress as a phenomenon threatening their job perspectives (European Commission, 2017a). While there is an increasing empirical evidence showing positive effects of robot adoption on productivity (Dauth et al., 2017; Graetz & Michaels, 2018; Jungmittag & Pesole, 2019; Kromann et al., 2020), research on the impact of this technology on the labour market is mainly limited to employment and wages (Acemoglu & Restrepo, 2020a; Borjas & Freeman, 2019; Chiacchio et al., 2018; Dahlin, 2019; Dauth et al., 2017; Graetz & Michaels, 2018; Jäger et al., 2016; Klenert et al., 2020; Koch et al., 2019). To the best of our knowledge, general evidence on other non-monetary aspects of job quality is lacking.

The aim of this paper is to explore whether the increase of robot density in Europe affects working conditions. This is relevant for two reasons: At first, workers do care for working conditions. Workers are willing to trade money for improvements in other domains in the sense of compensating differentials (Clark, 2015; Maestas et al., 2018; Muñoz de Bustillo et al., 2011), even if labour market imperfections and job rationing do not guarantee that the market compensates such attributes according to workers' preferences (Bonhomme & Jolivet, 2009). Working conditions are one of two most important concerns for European citizens (European Commission, 2017b): more than a half of them reported that the quality of work has worsened during the last years.

Second, other than business cycle fluctuations or changes in bargaining conditions, the introduction of (industrial) robots should in principle modify working conditions directly: specific tasks of workers are substituted, new tasks are created, others are reshaped; as a result, the whole production process changes with obvious consequences for job quality and working conditions. Because of these potentially contradictory changes in tasks, it is not clear in what directions they may change working conditions. While robots will substitute heavy and monotonic work—thus leading to less physical demands on employees—, work pace and stress might become stronger. The raise in productivity due to robot adoption might also result in a wider space for improving conditions at the workplace, which, in turn, are shaped by the possibility of monitoring workers' performance (Bartling et al., 2012). At the same time, robot adoption might widen the ability to improve employee surveillance, with consequences on work intensity.

We combine sector- and industry-level data on robots with several European-level surveys on working conditions that allow us to analyse how the increase in robot density affects working conditions at the local labour market. We use composite indices of job quality previously employed in the literature and use Ordinary Least Squares (OLS) in changes over the period 1995-2005. As there might be reverse causality or a problem with missing variables, we resort to instrumental variables (IV) techniques based on sector-level trends in robot adoption in other leading countries, such as South Korea, Switzerland or Australia. Whatever method we use, we find that the increase in robot adoption across Europe had a negative effect on job quality in work intensity but does not have any effect on other aspects of job quality, like physical job environment and skills and discretion of workers on the job.

Robots applied in the industrial production process are not so widespread as computers or potential applications of artificial intelligence. Therefore, it is debatable to which extent the deepening in the adoption of this technology represents a qualitative change (as one could more easily argue, for instance, regarding artificial intelligence, see Acemoglu and Restrepo (2020b) and Fernández-Macías et al. (2020)); so the impact of robots might not be the same as in the case of other technologies the literature has analysed thoroughly (see, Acemoglu and Autor [2011], Autor [2015], Autor and Salomons [2018], Barbieri et al. [2019], Fernández-Macías and Hurley [2016] and Jerbashian [2019]).

With our research we contribute to several recent discussions. There is a growing literature on the impact of robotization on employment and wages, which is far from reaching a consensus. While several studies for the US suggest a negative impact on employment and wages (Acemoglu & Restrepo, 2020b; Borjas & Freeman, 2019; Dahlin, 2019), the effects are not so clear for other economies. Those negative effects only seem to apply to manufacturing in Germany (Dauth et al., 2017), while the work of Chiacchio et al. (2018) for six EU countries only shows a detrimental impact on employment, but not for wages. The pioneering study of Graetz and Michaels (2018), including a wide set of developed countries, identifies a positive effect on wages and a neutral effect on employment, whereas Klenert et al. (2020), which extend the period of analysis and limit their exploration to manufacturing, even point out a positive contribution of robots to employment growth.[1] Similarly, the cross-country studies of Carbonero et al. (2018) and De Backer et al. (2018) draw mixed conclusions on the impact of robots on job cre-

[1] See also Bekhtiar et al. (2020) and Fernández-Macías et al. (2020) on problems with industry-level data.

ation. Firm-level studies, on the other hand, find a positive association between the introduction of robots and employment growth in France (Domini et al., 2020) and Spain (Koch et al., 2019). Our study is the first to explore the impact of robots on non-monetary working conditions.

Robots might affect job quality through several channels. In the first place, they can modify the tasks performed by workers. In principle, this effect can be more direct on those workers complementary to robots than those who are potentially replaceable. Nevertheless, the presence of robots might also create pressure on the work carried out by other workers, who might have to take up or modify the way they perform their (new) tasks due to the introduction of the technology. Furthermore, the introduction of a new technology might lead to productivity gains that lead not only to wage gains but also to the improvement of other job amenities, even if they are costly for employers.

We also contribute to the discussion about changes in working conditions. Fernández-Macías et al. (2015) show that job quality in the EU was remarkably stable before and after the financial crises with some increase in job quality in the European periphery. Green et al. (2013) look at different components of working conditions and find the component of work intensity and – to some extent – working time quality to improve in Europe. Moreover, they study the dispersion of these measures across groups and across time. Bryson et al. (2013) investigate the impact of organisational changes and trade unions on working conditions, whereas Cottini and Lucifora (2013) explore the consequences of working conditions on mental health. Closer to our topic are studies relating changes in computer use with working conditions: Menon et al. (2020) report that computerization has no large effects on working conditions in general, there is even a mild positive effect on job discretion. Green and McIntosh (2001) in an earlier study show that computer use leads to an intensification of the workpace.[2] In our study we extend this analysis with a closer look at the impact of robotization on working conditions in general.

Following this introduction, the rest of the paper unfolds as follows. Section 2 describes the databases employed in the analysis and outlines the identification strategy used in the econometric analysis. We present the main results of the paper in section 3 and the 4$^{\text{th}}$ and last section summarizes and discusses the main conclusions of the paper.

2. Data and methods

2.1. Data

Robots. In order to assess the effect of robotization on the working conditions of European workers, we combine several databases that contain information on robot adoption and job attributes. Our first source is the World Robotics 2017 edition, a dataset administered by the International Federation of Robotics (IFR) (IFR, 2018), the main association of manufacturers of robots worldwide. It comprises information on industrial robot stocks and deliveries by country and sector of activity all over the world from 1993 to 2016. The robots included in the IFR (2018) consist of industrial machinery, digitally controlled, mainly aimed at handling operations and machine tending, welding and soldering and assembling and disassembling. In terms of accounting, these robots are part of non-information

[2]There is a large literature on job satisfaction or happiness as general indicators of working conditions (see Clark and Oswald [1994] or Clark [2005] for early references). These indicators may lack comparability as they may also comprise differences in expectations (Osterman, 2013); they are general indicators and there is no research linking these indicators to robots.

and communication technology capital, with the exception of their associated software needed to manage them.[3]

The IFR basically constructs a series of robot stocks on the basis of deliveries, using a perpetual-inventory approach and a 12-year depreciation. This is a more reliable approach —as compared to using stocks—, since the association of robot producers controls those inflows directly. As the distribution of robots is missing in some years and countries, we impute initial unspecified stocks or deliveries on the basis of the distribution by industry in the three closest years to the period of interest with specified information.[4]

Working Conditions. We use the 2$^{\text{nd}}$, 3$^{\text{rd}}$ and 4$^{\text{th}}$ waves the European Working Conditions Survey (EWCS), carried out in 5-year intervals by the European Foundation for the Improvement of Living Conditions (Eurofound) (Eurofound, 2018), 1995, 2000 and 2005.[5] There are two additional waves (2010 and 2015), but we focus on the period 1995–2005 in order to avoid confounding effects of the Great Recession, which had a markedly different impact across countries and regions (Acemoglu & Restrepo, 2020a; Chiacchio et al., 2018; Dauth et al., 2017). Furthermore, the increase in robot density during the decade 1995–2005 is significantly more intense than over the period 2005–2015. For our sample countries, the number of robots per thousand workers rose from 0.800 in 1995 to almost 2.200 in

[3]IFR (2018) provides robot figures by industry according to the International Standard Industrial Classification of All Economic Activities, Revision 4, which is largely compatible with the Statistical Classification of Economic Activities in the European Community, Revision 2 (NACE Rev. 2).

[4]This process is very similar to the one followed by Graetz and Michaels (2018). They use the total number of specified deliveries for imputation (instead of the three closest years). Our series are virtually identical. For more details on the imputation procedure, see Fernández-Macías et al. (2020).

[5]We do not include the first wave of the EWCS, because of limited coverage of countries and reduced sample size.

2005; with only a slight increase to 2.750 in 2015. Finally, as there is less variation in the latter period, our proposed instrumentation (IV) strategy does not produce a significant first stage.

The EWCS represents the most comprehensive database for the analysis of non-monetary working conditions across Europe on a comparative perspective, covering the European Union (EU) members, several accession countries and other states like Norway and Switzerland. We focus on the 12 EU countries with the highest ratio of robots per worker during the analysed period.[6]

Each wave includes a minimum of 1,000 interviewees in each country and year. As robot technology is mainly used in manufacturing, we focus on privately salaried workers employed in mining and quarrying and the secondary sector (manufacturing, electricity, gas water supply and construction), which concentrates more than 90% of these types of robots. Unfortunately, there is no further disaggregation of these industries. This leaves us a sample of 7,764 workers. The EWCS contains a rich set of variables covering different dimensions of working conditions; we describe that in the next subsection.

Control Variables. We use the European Union Labour Force Survey (EU-LFS) (Eurostat, 2018) and due to missing regional information for Germany the European Community Household Panel (ECHP) for the years 1995 and 2000 (Eurostat, 2003).[7] Changes in information, communication and technology (ICT) capital stock per worker are from the EU KLEMS (Stehrer et al., 2019), data for Chinese imports come from the United Nations International Trade Statist-

[6]The list of countries includes Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Portugal, Spain, Sweden and the United Kindgom.

[7]Detailed information by region and industry sometimes was only available through an ad hoc request to the Eurostat User Support (Eurostat, 2020). Moreover, sectors have to be reclassified from NACE Rev. 1.1 to NACE Rev. 2.

ics Database, to which we access through the World Integrated Trade Solution (WITS) (World Bank, 2020) following Autor et al. (2013).[8]

We construct instrumental variables from the Korean Industrial Productivity Database (KIP), provided by the Korea Productivity Center (KPC) (KPC, 2015), labour force statistics from Australia and information from Eurostat for Switzerland.

Our database on working conditions, the EWCS, does contain detailed information on sectors of activity (only some large industry groups are available), but it is representative by region. In the fashion of previous literature (Acemoglu & Restrepo, 2020a; Dauth et al., 2017), we perform the analysis at such a level. In order to calculate the change in robot exposure by region, assuming that the distribution of the change in robot stocks by region over a certain period of interest depends on the distribution of employment at the beginning of the period, we combine detailed sector-level data by country on robots and region-level employment data by industry obtained from several ad hoc requests to the Eurostat User Support (Eurostat, 2020).[9] We provide further details on the construction of the variation

[8]Previous literature finds relevant negative effects of exposure to Chinese imports not only on employment and wages (Autor et al., 2016), but also on health outcomes (Lang et al., 2019).

[9]We consider 20 sectors of activity (in the nomenclature of NACE Rev. 2) we are able to match in our robot and employment data: agriculture, hunting and forestry; fishing (A); mining and quarrying (B); food products and beverages; tobacco products (C10–12); textiles, leather, wearing apparel (C13–15); wood and wood products (including furniture) (C16); paper and paper products; publishing and printing (C17–18); chemical products, pharmaceuticals, cosmetics, unspecified chemical, petroleum products (C19–21); rubber and plastical products (C22); glass, ceramics, stone, mineral products not elsewhere classified (C23); basic metals (C24); metal products (except machinery and equipment) (C25); electrical/electronics (C26–27), industrial machinery (C28); automotive (C29); other transport equipment (C30), other manufacturing branches (C32); electricity, gas and water supply (D, E), construction (F), education, research and development (P) and others. The questionnaires of the EU-LFS effectively collects this detailed information on the distribution of the labour force by region and industry, but the anonymized microdata does not disclose it because of confidentiality reasons and we access it to several tailored petitions.

in the robot exposure by region in the next subsection.

2.2. Methodology

As mentioned above, our identification strategy exploits the regional variation in the increase in the adoption of robots. Following the strategy proposed by Acemoglu and Restrepo (2020a), we compute the change in the exposure to robotization by region assuming that the robot inflows during a certain interval of time follows the distribution of employment in the initial period. Our geographical units of analysis mainly correspond to the Nomenclature of Territorial Units for Statistics at the second level (NUTS 2), although in some cases, because of the existence of administrative changes in the boundaries of NUTS we cannot trace over time, we make use of larger geographical units. As a result, we are able to trace 80 regions over the period 1995–2005. Given the very low mobility across NUTS 2 in Europe (Gákova & Dijkstra, 2008; Janiak & Wasmer, 2008), we can consider our regions as reasonably closed labour markets, in the sense that it is not likely that robot adoption results in relevant outflows from regions with high deployment to others with low adoption of the technology.

Another problem that might arise is a sort of sample selection bias. We concentrate our analysis on workers in these regions in the years 1995, 2000 and 2005. If the exposure to robots would change or reduce the workforce considerably, we would be in trouble, comparing working conditions of those in the region before the advent of robots with the working conditions of those still employed in the region after the exposure to robot adoption. While Acemoglu and Restrepo (2020a) do find a negative impact of robots on employment in the US, studies for Europe do not find such effects (Antón et al., 2020; Dauth et al., 2017). In addition, we use additional variables to control for changes in the composition of the workforce.

The main variable of interest in our analysis is the increase in robot exposure (RE), which we define as the change in the number of robots during a certain period t in a region r divided by the number of workers in the region at the beginning of the period, that is,

$$\Delta RE_{rt} = \frac{1}{L_{rt}} \sum_{j} \frac{L_{rjt}}{L_{jt}} \Delta R_{jt} \tag{1}$$

where R_{jt} represents the change in robot stocks in sector j in the country where the region is located over period t; L_{rt}, the initial number of workers in the region at the beginning of the period of interest; L_{jt} denotes the employment figures in industry j in region r in the initial year and L_{rjt}, the number of workers in region r in industry j at the same moment of time. In this fashion, we attribute to each region a change in the stock of robots according to the share of employment in this sector in the initial period.

In order to explore the impact of robot adoption on working conditions, we estimate the following equation:

$$\Delta Y_{rt} = \beta_0 + \Delta RE_{rt}\beta_1 + Z'_{rt}\beta_2 + \varepsilon_{rt} \tag{2}$$

ΔY_{rt} denotes the change in the average job quality indicator of region r over the period t. Z'_{rt} is a set of start-of-the-period regional control variables, very similar to those considered by Acemoglu and Restrepo (2020a) and Autor et al. (2013), including the share of employment in mining and quarrying and the secondary sector in the region (to which we refer as the share of industry for brevity), population (in logs), share of females and foreign workers, age structure of the workforce, the share of population with middle or high education, the average routine task intensity (RTI) (Autor & Dorn, 2013; Goos et al., 2014; Mahutga et al., 2018; Schmidpeter & Winter-Ebmer, 2020) and the average offshoreability risk (Blinder & Krueger, 2013; Mahutga et al., 2018).[10] Given that we pool two 5-year differences, we include time fixed effects covering each of those periods. Second, we add a geographical dummy for core-periphery countries to capture group-of-countries-specific time trends.[11]. Finally, it is possible that some changes in working conditions have to do with changes in the labour force composition. In order to mitigate this selection effect, we control for the changes in the share of female workers, the proportion of workers with medium education, the proportion of workers with high education and the share of workers aged less than 30 years old and aged 50 years old or more employed in the region in the industries considered in the analysis.

Similar to previous analyses of the impact of robotization on employment or wages (Acemoglu & Restrepo, 2020a; Dauth et al., 2017)), there is the possibility of reverse causation. In these studies it may well be that robot adoption is caused by developments on the labour market, like the availability of suitable workers or a fast rising wage in the respective sector. In our case, reverse causation could occur for similar considerations: Since working conditions can also be indirect cost components (slower work pace or costs for accident avoidance) or have an

[10]The aim of controlling for the initial values of RTI and offshoreability is to rule out that other sources of labour market changes due to technological changes different from robot adoption might conflate with the latter. The RTI intends to capture to which extent an occupation is routine-task intensive. The logic behind the RTI measure is that automation is more likely to affect routine, manual, non-interactive job tasks. Likewise, the offshoreability risk index tries to measure the degree to which a certain occupation might be outsourced to a remote location.

[11]We are unable to include country dummies given that some states only contain one traceable region because of their size or changes in the boundaries of NUTS2.

impact on labour supply with respect to a specific industry, reverse causation could apply. Given our use of non-monetary working conditions, the argument for reverse causation is less strong as in the case of wages. Still, we use the same strategy as Acemoglu and Restrepo (2020a) and Dauth et al. (2017), who instrument the adoption of robots by the trends in other developed countries.[12] Given our focus on European Union countries, we look at the patterns of robotization by sector in South Korea, one of the world leaders in the adoption of this technology (IFR, 2018; United Nations Conference on Trade and Development, 2017), in order to build our IV. Considering the size of this economy and its limited integration with EU countries (compared to other member states), it is not likely that Korean industry-level developments trigger any relevant general-equilibrium effects. The exclusion restriction of the IV strategy requires that the instrument (robotization in Korean industries) has no impact on European working conditions over and above its indirect impact via robotization in Europe. We strongly believe that this is, indeed, the case. We also build on data from Australia, Switzerland and Sweden in order to check the robustness of our results using alternative instruments.

We can express the increase in robot exposure as a function of the importance of each industry in the region and the average increase in robot density per worker at the national level. In order to build our IV, we consider the increase in robot exposure per worker in each of our third countries instead of the variable corres-

[12] It is worth mentioning that previous studies using robot data from the IFR to explore the impact of this technology on labour market outcomes find very close OLS and IV estimates (Acemoglu & Restrepo, 2020a; Dauth et al., 2017; Graetz & Michaels, 2018), thus suggesting little evidence of endogeneity in the first place.

ponding to each European Union country, obtaining the following expression:

$$\Delta RE_{rt}^{k} = \frac{1}{L_{rt}} \sum_{j} L_{rjt} \frac{\Delta R_{jt}^{k}}{L_{jt}^{k}} \tag{3}$$

where the superindex k denotes the third country used for building the IV (South Korea, Australia, Sweden or Switzerland). Our IV is relevant, with an F-statistic between 40 and 80 in different econometric specifications, using clustered standard errors at the regional level.

In order to build changes in ICT capital stock per worker and in the exposure to Chinese imports, we depart from sector-level data and follow a similar procedure to the one applied to robots based on the initial distribution of employment, considering roughly the same industry classification as in the case of robots and even a more detailed one regarding Chinese imports.

Working conditions in the EWCS are referring to the dimensions i) work intensity, ii) physical environment and iii) skills and discretion, which are developed by Eurofound and their collaborators (see, e.g., Eurofound [2012, 2015, 2019], Fernández-Macías et al. [2015], Green et al. [2013], Menon et al. [2020], and Muñoz de Bustillo et al., 2011). We formulate indicators in such a way, that all questions are available in the three waves of the survey.

The index of work intensity comprises two sub-dimensions, quantitative demands and pace determinants and interdependency. The first sub-dimension builds on three variables, pace of work (high speed), tight deadlines and time pressure, while our indicator of pace determinants and interdependency considers how interviewee's work depends on colleagues, customer demands, production targets, machine speed and bosses.

Job quality in physical environment considers three domains: ambient risks (vibrations, noise, high temperatures and low temperatures), biological and chemical risks (exposition to fumes and vapours and chemicals) and posture-related risks (tiring positions, heavy loads and repetitive movements).

Finally, the quality of work in terms of skills and discretion comprises three sub-dimensions: cognitive tasks (carrying out complex tasks and working with computers, smartphones, laptops, etc.), decision latitude (control the order of tasks, speed of work, methods of work and timing of breaks) and training (receiving training provided by the employer and the possibility of learning new things).

Following the previous literature (see, e.g., Eurofound [2019]), we combine these variables, most of them of an ordinal nature, in order to define indicators of job quality in each of the dimensions and sub-dimensions in a positive sense—i.e., the higher the measure, the higher the well-being—and using a 0–100 scale. For instance, the attribute *vibrations* receives the highest score when the workers are never exposed to this sort of workplace risk. Each variable receives the same weight within each sub-dimension and we compute the arithmetic average of these sub-domains in order to again obtain a score between 0 and 100 for our index of job quality in work intensity.[13]

3. Results

Table 1 displays descriptive statistics of the dependent variables and covariates of our database, containing 80 European regions. We present the figures for the

[13]Sensitivity analyses in Muñoz de Bustillo et al. (2011) suggests that the composite measures of these dimensions are quite robust to the use of different weighting schemes because there is a high positive correlation between the outcomes in different domains

three mentioned dimensions (work intensity, physical environment and skills and discretion) and the two sub-domains composing work intensity. The evolution of these variables over time does not seem to follow a clear pattern. The number of robots per worker by region multiplies by more than 2.5 from 1995 to 2005. Figure 1 plots the correlation between 5-year changes in robot exposure and changes in job quality by dimension over the period 1995–2005. The graphs suggest a negative correlation in the case of work intensity, a somewhat weaker negative one with physical environment and a slightly positive one with respect to skills and discretion.

We present the main results of our analysis of the effects of robot adoption on work intensity, physical environment and skills and discretion in Tables 2 and 3, respectively. In these tables, we display both OLS and IV estimates, without and with controls for the change in the share of workers of different characteristics in the working population in the region. The relevant F-statistic of the first stage is well above 50, pointing out to the relevance of our IV. We present the complete details on the first stage in Table A.1 in the Appendix.

Table 2 shows that the adoption of robots reduces job quality with respect to work intensity. All four estimates are very consistent, columns (1) and (2) excluding or including variables for compositional change in the workforce show an effect of -4.3, whereas the IV results are somewhat higher at -5.2–-5.6; the statistical indistinguishability between OLS and IV results indicates no big relevance for endogeneity. The quantitative result means that an increase in robot adoption of one unit (which is around one standard deviation in 2000) increases work intensity by 4–5 units (60–80 percent of a standard deviation in 2000). In other words, the increase in robots between 1995 and 2005 from $0.8 - -2.1$ per thousand workers led to an increase in work intensity of 5.6–7.3 points (87–114 percent of a standard deviation in 2000). These effects are rather large, but comparable to those of Menon et al. (2020) in size: They calculate the effect of computers on working conditions in the European Union, finding negative but insignificant coefficients for the impact of computer use on work intensity, but a positive impact of computer use on work quality in terms of work discretion.

Table 3 reports similar estimations for working conditions in terms of physical environment and skills and discretion. Panel A of the Table refers to physical environment and Panel B to skills and discretion. Here, the effects are smaller, mostly negative (i.e., reducing job quality) and insignificant. This refers to both OLS and IV results: Physical environment and skills and discretion are not impacted by the adoption of robots.

We have seen that there is a negative effect of robotization on job quality, but only in the dimension of work intensity, not in physical environment and skills and discretion. In Table 4 we further proceed by looking at the sub-domains of work intensity, quantitative demands and pace and interdependence. Again, we present OLS and IV coefficients, which are fairly consistent. Both dimensions of work intensity are negatively related with robotization. The impact on the sub-dimension of quantitative demands is considerably stronger than in the whole job quality dimension, while the effect in the case of pace and interdependency is somewhat weaker, but still statistically significant.

In order to check the robustness of our main results, we perform several additional estimations whose results are presented in Table 5. In the first two columns, we test whether our results hold under the use of other instruments: in column (I) we use two countries outside the European Union not included in our sample of regions, Australia and Switzerland. Under this specification, the effect of robot adoption remains negative and significant. In column (II), we use the increase in robot penetration by sector in Sweden (one of the leaders in the adoption of this technology in Europe) in order to build our IV. In this case, we have to exclude Sweden from the countries considered in the analysis. Our results are pretty similar to the ones reported under our original instrument based on South Korea.

In the third column, we include two additional controls that, though being potentially endogenous, have been shown to influence labour market outcomes: the increase in exposure to Chinese imports and the increase in the ICT capital per worker. Moreover, they could correlate with the adoption of robots. Results have to be taken with care, therefore. The estimates in column (III) show that the baseline results do not qualitatively change when adding these additional covariates, corroborating our main results.

The final robustness check is a rough "falsification" test, where we look at the effects of the change in robot exposure per worker in the region on workers in agriculture, forestry and fishing and the services sector. Given that most of the robots are concentrated in manufacturing, we should expect a null or, at least, a much lower impact of robots on the job quality of workers employed there. If our results were based on other concurrent events—correlated with robot adoption—such a placebo might catch these concurrent events. As expected, and in contrast to such a hypothesis, there is no effect of robotization in this falsification exercise (column (V)).

We present similar robustness checks for the impact of robotization on job quality in the dimensions, physical environment and skills and discretion in the Annex (Tables A.2 and A.3). These results are very similar to those presented in Table3 and do not show any effect of robotization on either the physical environment of the job or skills and discretion in the job.

4. Conclusions

The impact of technology on the workplace, workers and their work environment attracts a lot of concern among citizens and researchers in Social Sciences, alike. The adoption of industrial robots, even if not new, is one of the more visible realizations of such technological changes. While there are a relevant number of studies concerned with the impact of this technology on employment and wages, ours is the first comprehensive study on the impact of robotization on working conditions in Europe. We employ data from the European Working Conditions Survey and instrumental variables techniques in order to explore how a more intense adoption of this technology shapes job quality in regional labour markets. Over the period 1995 to 2005 an increase in robots used in industry led to worse working conditions with respect to tougher work intensity, but there are no effects on other working conditions, like physical environment of the job or skills and discretion in the job. While robots are substituting for arduous—repetitive, heavy or fatiguing—tasks, their precision and predictability and standardization may lead to an increase in work intensity.

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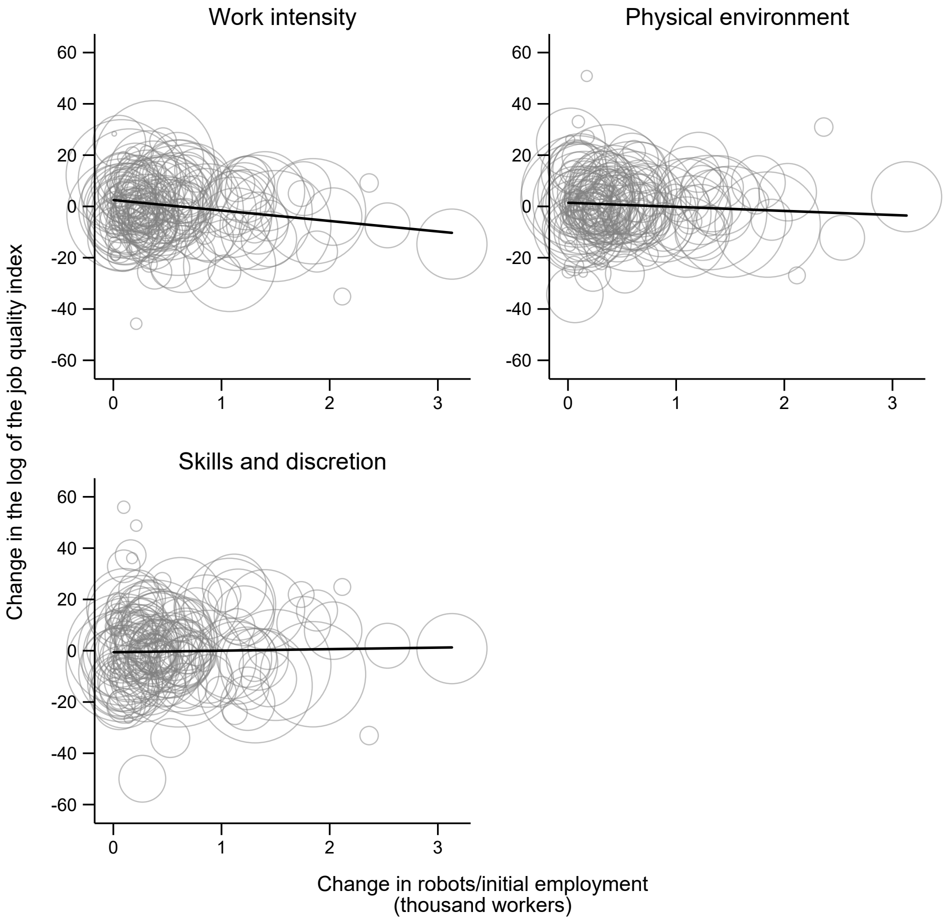
Figures and tables

Figure 1. Job quality index of work intensity and robot exposure (5-year differences, 1995–2005).



Note: Observations weighted by the number of workers in the region at the beginning of the period.
Source: Authors' analysis from EWCS, EU-LFS and IFR.

Table 1. Descriptive statistics

	Means (standard deviations)		
	1995	2000	2005
Robots per thousand workers	0.798	1.486	2.126
	(0.585)	(1.192)	(1.672)
Work intensity (0–100)	55.459	55.374	55.710
	(6.969)	(6.428)	(7.153)
Quantitative demands (0–100)	59.305	59.878	63.741
	(9.991)	(7.996)	(7.500)
Pace and determinants (0–100)	51.574	50.859	47.661
	(7.830)	(9.353)	(9.648)
Physical environment (0–100)	72.602	70.092	72.431
	(6.441)	(6.889)	(5.916)
Skills and discretion (0–100)	55.595	53.409	53.570
	(9.659)	(9.290)	(11.255)
% of pop. employed in industry	0.301	0.297	0.283
	(0.060)	(0.067)	(0.064)
Population (thousand people)	7,061.838	7,939.785	8,014.270
	(4,949.596)	(5,232.782)	(5,111.177)
% of females	0.498	0.498	0.499
	(0.009)	(0.009)	(0.007)
% of pop. above 64	6.654	6.151	5.855
	(0.941)	(0.909)	(0.870)
% of pop. with medium education	0.412	0.403	0.420
	(0.127)	(0.123)	(0.120)
% of with high education	0.168	0.176	0.206
	(0.065)	(0.063)	(0.067)
% of foreigners	0.063	0.085	0.073
	(0.056)	(0.064)	(0.064)
Average RTI index	0.108	0.090	0.031
	(0.090)	(0.106)	(0.071)
Average offshorability index	0.022	0.012	−0.052
	(0.109)	(0.122)	(0.098)
% of female workers	0.215	0.221	0.236
	(0.117)	(0.106)	(0.051)
% of workers below 30	0.224	0.212	0.238
	(0.123)	(0.121)	(0.038)
% of workers with 50 or more	0.193	0.236	0.201
	(0.127)	(0.154)	(0.040)
% of medium educated workers	0.404	0.429	0.473
	(0.178)	(0.189)	(0.162)
% share of highly educated workers	0.273	0.233	0.173
	(0.263)	(0.206)	(0.078)
ICT capital stock (thousand US$ per worker)	7.720	6.311	7.198
	(2.513)	(1.556)	(1.450)
Chinese imports (US$ per worker)	1,464.923	3,068.354	8,001.657
	(630.298)	(1,695.555)	(4,977.016)
	80	80	80

Notes: Observations weighted by the number of workers in the region.
Source: Authors' analysis from EWCS, ECHP, EU-LFS, IFR, EU KLEMS and WITS.

Table 2. Effect of robot adoption on job quality: work intensity

	(I) OLS	(II) OLS	(III) IV	(IV) IV
ΔRobot exposure	−4.382***	−4.292***	−5.592***	−5.166***
	(1.256)	(1.252)	(1.953)	(1.628)
% of employment in industry	30.040*	24.961	32.580**	26.373
	(16.480)	(17.756)	(16.619)	(17.611)
Population (log)	2.187**	1.718**	2.099**	1.677**
	(0.940)	(0.845)	(0.924)	(0.839)
% of females	6.241	−57.528	−6.887	−68.191
	(67.022)	(89.371)	(69.779)	(93.323)
% of pop. above 64	0.657	0.660	0.614	0.613
	(0.565)	(0.723)	(0.568)	(0.726)
% of pop. with medium education	19.104**	13.856*	20.237***	14.681*
	(7.562)	(7.887)	(7.718)	(7.999)
% of pop. with high education	75.508***	55.904***	75.436***	55.443**
	(19.239)	(21.365)	(19.222)	(21.708)
% of foreigners	−3.936	−1.568	−1.438	0.061
	(10.891)	(14.330)	(10.682)	(14.559)
RTI	24.790**	10.805	23.308**	9.575
	(10.190)	(13.101)	(10.198)	(13.439)
OFF	−20.178	−10.606	−17.679	−8.780
	(12.920)	(13.946)	(13.244)	(14.294)
R^2	0.181	0.267		
No. of observations	160	160	160	160
Mean of dependent variable	0.015	0.015	0.015	0.015
Mean of independent variable	0.607	0.607	0.607	0.607
First-stage Wald F statistic			75.304	59.089
Compositional changes		✓		✓

Notes: *** significant at 1% level; ** significant at 5% level; * significant at 10% level. All specifications include an intercept, a dummy for the period 2000-2005 and a dummy for core-periphery European countries. 5-year changes, 1995-2005. Standard errors clustered at the regional level in parentheses. Observations weighted by the number of workers in the region.
Source: Authors' analysis from EWCS, ECHP, EU-LFS, IFR and KIP.

Table 3. Effect of robot adoption on job quality: physical environment and skills and discretion

	(I) OLS	(II) OLS	(III) IV	(IV) IV
Panel A. Physical environment				
ΔRobot exposure	−0.053	−0.062	−1.727	−1.544
	(1.481)	(1.402)	(2.061)	(1.892)
R^2	0.149	0.183		
No. of observations	160	160	160	160
Mean of dependent variable	0.463	0.463	0.463	0.463
Mean of independent variable	0.607	0.607	0.607	0.607
First-stage Wald F statistic			75.304	59.089
Panel B. Skills and discretion				
ΔRobot exposure	−0.558	0.224	−3.284	−2.208
	(1.963)	(1.769)	(3.067)	(2.546)
R^2	0.085	0.107		
No. of observations	160	160	160	160
Mean of dependent variable	0.463	0.463	0.463	0.463
Mean of independent variable	0.607	0.607	0.607	0.607
First-stage Wald F statistic			75.304	59.089
Start-of-period-controls	✓	✓	✓	✓
Compositional changes		✓		✓

Notes: *** significant at 1% level; ** significant at 5% level; * significant at 10% level. All specifications include an intercept, a dummy for the period 2000-2005 and a dummy for core-periphery European countries. 5-year changes, 1995-2005. Standard errors clustered at the regional level in parentheses. Observations weighted by the number of workers in the region.
Source: Authors' analysis from EWCS, ECHP, EU-LFS, IFR and KIP.

Table 4. Effect of robot adoption on the sub-dimensions of work intensity

	Quantitative demands		Pace and interdependency	
	(I) OLS	(II) IV	(III) OLS	(IV) IV
ΔRobot exposure	−6.200***	−6.806***	−2.354*	−3.528*
	(1.678)	(1.965)	(1.257)	(1.933)
No. of observations	160	160	160	160
R^2	0.319		0.320	
Mean of dependent variable	2.254	2.254	−2.215	−2.215
Mean of independent variable	0.607	0.607	0.607	0.607
First-stage Wald F statistic		59.089		59.089
Start-of-period controls	✓	✓	✓	✓
Compositional changes	✓	✓	✓	✓

Notes: *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors clustered at the regional level in parentheses. All specifications include an intercept, a dummy for the period 2000-2005 and a dummy for core-periphery European countries. 5-year changes, 1995-2005. Observations weighted by the number of workers in the region.
Source: Authors' analysis from EWCS, ECHP, EU-LFS, IFR and KIP.

Table 5. Robustness checks: work intensity

	Alternative IVs (AUS, CH)	Alternative IV (SE)	Additional controls	Unweighted	Falsification test
	(I)	(II)	(III)	(IV)	(V)
ΔRobot exposure	−3.853**	−4.623***	−6.727***	−3.412*	1.370
	(1.585)	(1.667)	(1.854)	(1.883)	(1.227)
No. of observations	160	158	150	160	160
Mean of dependent variable	0.015	−0.078	0.103	0.563	0.324
Mean of independent variable	0.607	0.610	0.626	0.483	0.533
First-stage Wald F statistic	63.259	47.830	51.351	68.405	88.478
Hansen J p-value	0.418				
Start-of-period controls	✓	✓	✓	✓	✓
Compositional changes	✓	✓	✓	✓	✓
Chinese import exposure			✓		
ΔICT capital			✓		

Notes: *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors clustered at the regional level in parentheses. All specifications include an intercept, a dummy for the period 2000-2005 and a dummy for core-periphery European countries. 5-year changes, 1995-2005.

Source: Authors' analysis from EWCS, ECHP, EU-LFS, IFR, KIP, Australian labour force statistics, EUKLEMS and WITS.

Annex

Table A.1. First-stage regression of the change in robot exposure on the change in robot exposure using the changes in sectoral robot density in South Korea

	(I)	(II)
ΔRobot exposure (South Korea)	1.053***	1.064***
	(0.116)	(0.130)
Share of industry	−0.505	−0.796
	(0.808)	(0.911)
Population (log)	−0.031	−0.037
	(0.025)	(0.027)
% of females	2.482	2.455
	(2.644)	(2.565)
% of pop. above 64	−0.053***	−0.053***
	(0.018)	(0.017)
% of pop. with medium education	1.458***	1.609***
	(0.322)	(0.349)
% of pop. with high education	0.212	−0.416
	(0.506)	(0.620)
% of foreigners	0.133	0.389
	(0.545)	(0.562)
RTI	−1.257***	−1.668***
	(0.294)	(0.348)
OFF	0.768**	1.082**
	(0.350)	(0.422)
Compositional changes		✓
R^2	0.849	0.856
No. of observations	160	160
Mean of dependent variable	0.607	0.607
Mean of the instrument	0.793	0.793
First-stage Wald F statistic	75.304	59.089
Partial R^2 of instrument	0.714	0.699

Notes: *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors clustered at the regional level in parentheses. All specifications include an intercept, a dummy for the period 2000-2005 and a dummy for core European countries. 5-year changes, 1995-2005. Observations weighted by the number of workers in the region.
Source: Authors' analysis from EWCS, ECHP, EU-LFS, IFR and KIP.

Table A.2. Robustness checks: physical environment

	Alternative IVs (AUS, CH)	Alternative IV (SE)	Additional controls	Unweighted	Falsification test
	(I)	(II)	(III)	(IV)	(V)
ΔRobot exposure	−1.027	−0.800	−0.554	−0.494	−0.759
	(0.808)	(0.861)	(0.943)	(1.083)	(0.836)
No. of observations	160	158	150	160	160
Mean of dependent variable	1.129	1.180	1.150	1.020	1.129
Mean of independent variable	0.533	0.535	0.545	0.533	0.533
First-stage Wald F statistic	69.779	80.617	77.916	84.135	88.478
Hansen J p-value	0.952				
Start-of-period controls	✓	✓	✓	✓	✓
Compositional changes	✓	✓	✓	✓	✓
Chinese import exposure			✓		
ΔICT capital			✓		

Notes: *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors clustered at the regional level in parentheses. All specifications include an intercept, a dummy for the period 2000-2005 and a dummy for core-periphery European countries. 5-year changes, 1995-2005.
Source: Authors' analysis from EWCS, ECHP, EU-LFS, IFR, KIP, Australian labour force statistics, EUKLEMS and WITS.

Table A.3. Robustness checks: skills and discretion

	Alternative IVs (AUS, CH)	Alternative IV (SE)	Additional controls	Unweighted	Falsification test
	(I)	(II)	(III)	(IV)	(V)
ΔRobot exposure	0.198	−0.382	0.826	2.073	−0.377
	(1.415)	(1.481)	(1.501)	(1.996)	(1.483)
No. of observations	160	158	150	160	160
Mean of dependent variable	−0.140	−0.247	−0.211	0.840	−0.140
Mean of independent variable	0.533	0.535	0.545	0.533	0.533
First-stage Wald F statistic	69.779	80.617	77.916	84.135	88.478
Hansen J p-value	0.904				
Start-of-period controls	✓	✓	✓	✓	✓
Compositional changes	✓	✓	✓	✓	✓
Chinese import exposure			✓		
ΔICT capital			✓		

Notes: *** significant at 1% level; ** significant at 5% level; * significant at 10% level. Standard errors clustered at the regional level in parentheses. All specifications include an intercept, a dummy for the period 2000-2005 and a dummy for core-periphery European countries. 5-year changes, 1995-2005.

Source: Authors' analysis from EWCS, ECHP, EU-LFS, IFR, KIP, Australian labour force statistics, EUKLEMS and WITS.