Robots, skills and temporary jobs: evidence from six European countries

Abstract:
In our analysis of the impact of robot adoption on the use of flexible contracts in six European countries, we find that control for the type of innovation model that is dominant in an industry is crucial. In a '*high* knowledge cumulativeness' innovation regime, robot adoption reduces the probability that *high*-skilled workers will receive temporary contracts, while no significant effect has been found for medium- and low-skilled workers. The rationale is: In a high cumulativeness regime, innovation depends on a firm's *internal* knowledge sources, and high-skilled (rather than medium- and low-skilled) workers are crucial carriers of knowledge. The situation is different in '*low*-cumulativeness' regimes. In the latter, firms are primarily using externally acquired knowledge in their innovation process. This makes workers more easily interchangeable and robot adoption significantly increases the probability to get temporary jobs for both medium and high-skilled workers, but leaves low-skilled workers unaffected.

JEL-codes: J3, J5, M5, O3

Key words: robots, temporary jobs, innovation regimes, knowledge cumulativeness

1 Introduction

So far, most empirical studies addressed the impact of robots on employment, skills reconfiguration and wages at the country-, industry- and firm-level (see, among others, Dixon et al., 2021; Acemoglu & Restrepo, 2020; Acemoglu et al., 2020; Koch et al., 2021; Graetz & Michael, 2018). But there is still scant evidence concerning the effects of robots on the *quality* of jobs, in spite of the European Commission (2020) raising concern about in-work poverty risks, low social security standards, and poor career perspectives of temporary workers.

To the best of our knowledge, only Destefano et al. (2019) directly cover atypical jobs in their study of industrial robot diffusion in Japan. They find that adoption of robots is associated with changes in the composition of employment due to the dismissal of non-regular employees. In an unpublished paper, Cuccu and Royuela (2022) find for Spain (years 2001-2017), that workers displaced by robot adoption find a new job but face a qualification downgrading and are more likely to be re-employed through temporary employment agencies. As for EU countries, Dauth et al. (2021), Bessen et al. (2019) and Humlum (2019), touch at this question. Evaluating the impact of automation at firm or individual level, they distinguish between incumbent/senior workers, mostly employed with open-ended contracts, and young workers/recent hires, on temporary contracts. They found mixed results. Depending on the national context, robotization may favour new hires of younger and high-skilled people performing tasks complementary to those taken over by robots, such as in the case of Denmark and the Netherlands (see Humlum, 2019 and Bessen et al., 2019, respectively). By contrast, in Germany, robotization does not favour younger and high-skilled workers but protects senior insiders (Dauth et al. 2021).

This paper addresses the impact of robots on the likelihood that people get a temporary or a permanent contract, covering six European economies (Belgium, Germany, France, Italy, Spain and the UK). The choice of these six countries (henceforth: SECs) is guided by the characteristics of worker-level and industry-level databases that we were able to combine. During the last decades, our SECs experienced a high speed of automation in production processes. In 2014, robots in our six countries amounted to 85% of all robots installed in the EU-28 (IFR, 2016).

In theory, robotization could substitute workers in a range of specific tasks and reduce employment (displacement effect). The efficiency gains of robot use, however, generate productivity effects and prompt compensation mechanisms, through price reductions, input-output linkages and final demand effects. Such effects may, in favourable cases, even expand employment or at least compensate part of the initial job destruction through a reinstatement effect (Acemoglu & Restrepo, 2019).

Based on our literature review in section 2, we conjecture that the overall impact of industry-level robot adoption as well as its mediating effect on the relationships between workers' ages, skills (captured by occupations), education and temporary contracts, depend on heterogeneity between industries. Drawing from the neo-Schumpeterian literature, we investigate the role of industry-level technological regimes in moderating those relationships, making use of work by Peneder (2010). His study distinguishes industries by the degree of 'cumulativeness of knowledge' that is required for the innovative process. Industries with a low cumulative knowledge base are primarily using external sources of knowledge, while high cumulative industries lean primarily on internally developed knowledge. We hypothesize that in industries with a high 'cumulativeness' of knowledge, robotization reduces temporary contracts, especially for high skilled and highly educated people. The rationale is that longer job tenures are attractive to employers as innovative competences depend on the firm's internal sources of knowledge, including worker-embodied (and often ill-codified) knowledge from experience (Kleinknecht, 2020).

The opposite may hold for industries with a *low* cumulativeness of knowledge. Relying more on *external* sources of knowledge the latter are less dependent on workers as carriers of critical knowledge. Therefore, robot adoption in such industries does not necessarily reduce rates of temporary jobs.

In our empirical part, we combine worker-level data from the *Structure of Earnings Survey (SES)* collected by *Eurostat* with industry-level data from the *International Federation of Robotics* (IFR, 2016) for robot exposure[i]. We estimate Probit models for the choice between temporary versus permanent jobs in our six European country-industries in 2006, 2010 and 2014. Our estimates take into account the potential endogeneity of robot adoption by implementing a Probit control function approach and using as an instrument the average robot exposure of Japan and South Korea, i.e., two Asian countries more advanced than our SECs in terms of robotization of production processes. We further perform robustness checks on the sensitivity of results to cross-country heterogeneity and international trade.

The paper proceeds as follows. Section 2 motivates our research and sketches our conceptual framework. Section 3 introduces the data and descriptive statistics. Section 4 focuses on the econometric strategy and the main results and robustness checks are reported in section 5. Section 6 concludes.

2 Motivation and Background

2.1 Preliminary observations

Robot density was growing slightly faster in our SECs than in the entire EU-28 (Figure 1). In the former, robots per thousand workers grew by 125% (from 1.19 to 2.68) while in the EU-28, growth was 113% (from 1 to 2.13). Concomitantly, in both SECs and EU-28, temporary contracts increased more than permanent ones. However, in the six countries, growth of temporary employees appears to be relatively lower and the gap in the cumulative growth of permanent and temporary workers tends to narrow. Indeed, between 1996 and 2014 the temporary vs permanent workers cumulative growth rate was 24% vs 18% in the SECs and 55% vs 36% in the EU-28. At first glance, one might draw the speculative conclusion that a higher speed of robot adoption in our six countries moderated the degree of labour market flexibilization. But these are of course highly aggregated descriptive data that do not inform us about causalities.

In our estimates below, we take account of the potential interference of structural and institutional differences among our six countries. For example, Spain shows exceptionally high shares of temporary workers in total employment (see Figure 2). Spain experienced labour market reforms at the margin in the 1980's that remarkably consolidated a dual labour market. The other countries show intermediate incidence of temporary employment that hovers around the EU-28 average.

FIGURE 1

FIGURE 2

2.2 Automation, temporary jobs and knowledge cumulativeness regimes: a conceptual framework

2.2.1 The reallocation of tasks between robots and labour

Literature on industrial robots often analysed the role of automation at *aggregate* levels and documented a complex relationship between technology and employment dynamics. Automation can destroy jobs as it substitutes labour in a range of tasks, but it also induces compensation mechanisms, activated by productivity gains, that may counterbalance the labour-saving effect (see Acemoglu & Restrepo, 2019, Dosi et al. 2021a). Acemoglu & Restrepo (2019) provide an overall explanation of the task-based mechanisms at work once robots become pervasive. On the one hand, automation always generates a productivity effect, and the resulting increase in value added may raise labour demand for non-automated tasks. Depending on the relationship between technology and tasks, robots may simply reallocate to capital tasks that were previously performed by labour, such that a *displacement* effect dominates. Alternatively, a number of new tasks are created or a refinement of former tasks pertaining to labour may emerge. Hence, *displacement* and *reinstatement* effects can have ambiguous effects on employment.

Graetz and Michael (2018) focus on European countries and find that robots did not significantly reduce total employment, although they reduced low-skilled workers' employment share.

Some recent studies, however, have pointed out that *aggregate* outcomes may mask significant heterogeneities at micro-level. For example, Bessen et al. (2019) find for The Netherlands higher firing rates among workers with long tenures, while no significant displacement effects emerged for workers with shorter average tenures (less than three years). Interestingly, they show that robot adoption turns out to be more labour-displacing than increasing use of IT.

Dauth et al. (2021) reached different conclusions by using matched employer-employee data in Germany. In Germany, manufacturing companies allocated tasks that are complementary to automation to workers with longer job tenures, thus achieving improvements in both the stability and the quality of their jobs. The authors also show that the negative effect of automation on manufacturing employment, between 1994 and 2014, was driven by smaller inflows of younger workers, rather than by layoffs of older incumbents. These results reflect protective labour market institutions as a mediator of the impact of technological change, thus explaining a *retainment effect* due to high firing costs. Note that the German system is often considered as 'patient capitalism': enduring relations are pervasive, the population of innovative firms is fairly stable (Breschi et al. 2000) and sectoral specialization takes place in manufacturing industries with 'creative accumulation' regimes (Malerba & Orsenigo 1996).

Koch et al. (2021) addressed heterogeneity of Spanish manufacturing firms, i.e., between adopters and non-adopters of robots. The authors show that ex-ante more skill-intensive firms are less likely to be early adopters, but ex-post these firms show higher productivity gains and higher survival rates than non-adopters. A significant shift of labour demand towards high-skilled occupations (technicians, researchers and engineers) has been documented for Denmark by Humlum (2019). Humlum partially builds upon the study by Acemoglu & Restrepo (2020) and links in a unique framework the two-sided evidence on firms (as done by Koch et al. 2021) and workers (Dauth, et al. 2021). Humlum does not explicitly distinguish between incumbent and newly hired workers, but the results suggest that younger workers with less specific skills and a long career ahead benefit from switching into high-skilled occupations, in line with Bessen et al. (2019).

Although these studies do not explicitly deal with the question of complementarity between robot adoption and temporary jobs, they offer useful insights. Depending on national labour market institutions and sectoral specialisation, robot-adopting firms may expand and reorganise labour by employing younger and high-skilled workers, possessing little firm-specific skills; these workers are likely hired as temporary workers, as indicated by Bessen et al. (2019) and Humlum, (2019) in the 'flexible' labour markets of The Netherlands and Denmark, respectively. Under more 'rigid' labour markets and where sectoral specialisation of countries relies on industries highly affected by robotization (as the car industry), firms introducing robots reallocate to new tasks their incumbent workers as in the German case reported by Dauth et al. (2021).

Notice, however, that to the best of our knowledge, there are no empirical investigations directly concentrating on the impact of robots on the *quality* of employment as expressed in different types of contracts. The only exception is Destefano et al. (2019) for Japan. This study, in line with Dauth et al. (2021), found that robot diffusion reduced the propensity to employ non-regular workers, i.e., part-timers and temporary employees. It should also be noted that part of the results described above are conditioned by a *reallocation effect*, because firms adopting automation technologies may gain market share at the expense of non-adopting firms, as found for Spain and France (see Koch et al. 2021, Acemoglu et al. 2020).

How robot adoption influences rates of temporary jobs at industry level may depend not only on national labour market institutions, but also on the interplay between characteristics of workers (age, skills and education) and on the innovation regime dominant in an industry.

2.2.2 Age, skills and education profiles of temporary jobs, robots and knowledge cumulativeness

In European countries, temporary employment is high for younger workers (15-29) endowed with the low educational attainment and employed in low-paid occupations (services and sales workers, elementary occupations). However, over the last years, the same countries experienced increasing shares of temporary workers with tertiary educational attainment and employed in higher paid occupations (technicians and professionals) as reported by Eurofound (2015, TableA.2; and 2020, Figure 5).

The literature on temporary jobs underscored that this kind of non-standard employment may serve as i) a 'stepping stone' towards more secure or stable employment or ii) simply is a 'dead end' (see Filomena and Picchio, 2022, for a recent review). In the 'stepping stone' case, temporary contracts are used as a screening device; in the dead-end case, these contracts are a flexible buffer to manage exceptional production peaks or simply represent the cheapest alternative to automation or other process innovations (Booth et al. 2002).

Another reason of why robot adoption in an industry may lead to increased rates of flexible personnel could come from non-robot-adopting firms using cheaper temporary employment as a survival strategy (the dead-end conjecture). This conjecture is supported by connecting two important strands of literature, i.e., the neo-dualist hypothesis of business firms (Dosi, 2008; Andrews et al., 2015; Dosi et al., 2021b) and the labour market dualism hypothesis (Blanchard & Landier, 2002; Boeri, 2011; Cappellari et al., 2012). According to the former, a polarization between technological laggards and leaders is emerging in some OECD countries, causing skewness in growth rate distributions, as is also observed by Foster et al. (2018) and Corrado et al. (2021). The technological leader group includes those modern and dynamic high-performing companies ('gazelles') that likely base their success on investing in the new wave of automation technologies; the laggard group is represented by a population of 'turtles′ that can survive only by adopting cheaper labour rather than new machines (Dosi et al., 2021b).

In parallel, the labour market dualism literature highlighted how reforms liberalising temporary contracts induced some firms to design routine and low productivity jobs that ease the employment of temporary workers (Blanchard & Landier, 2002); this type of reforms has been frequently associated with lower capital/labour ratios and lower investments (Cappellari et al., 2012). To the best of our knowledge, only Cuccu and Royuela (2022) analysed the different effects of automation along the skills' profile of (temporary) workers. In an unpublished paper they show for Spain that in industries highly exposed to robots, only displaced low and medium skilled workers have higher probability to be re-employed by means of temporary contracts, but not high skilled workers.

In the following, we propose that the impact of robot adoption on temporary jobs depends decisively on an industry's technological characteristics. Inter-industry heterogeneity has been explored by a literature investigating Schumpeterian patterns of innovation and knowledge cumulativeness (Malerba & Orsenigo, 1996; Breschi et al. 2000; Peneder, 2010) and the importance of technological regimes for the (negative) impact of more flexible labour relations on innovation (Cetrulo et al., 2019; Pieroni & Pompei, 2007; Kleinknecht et al., 2014) and on productivity (Vergeer et al. 2015). We make use of Peneder's (2010) taxonomy that concentrates on the degree of *'cumulativeness'* of knowledge. In high-cumulativeness regimes, innovative competences depend primarily on a firm's internal (and often tacit) knowledge from experience that tends to be ill-documented and is mainly embodied by workers. In industries with a *low* cumulativeness of knowledge, firms rely more on externally available (general) knowledge and competences.

Peneder's classification of industries is different from the Eurostat standard taxonomies, based on sectoral R&D investments and shares of high-skilled workers. Instead, Peneder’s taxonomy relies on a cluster analysis of Community Innovation Survey data on firms' reporting of the relative importance of internal versus external sources of knowledge to their innovations (see Peneder, 2010 for a more detailed discussion of the classification procedure).

Let us give two examples that illustrate how Peneder’s knowledge cumulativeness regimes moderate the effects of robots on temporary workers. We take two representative industries with a low versus a high cumulativeness of knowledge, i.e., the food and automotive industries. In the food industry, as shown by Lloyd and Payne (2021), the demand for new basic digital skills, required after introducing robotization technologies in surveying production processes, did not entail significant challenges or substantially greater skill demands. Both operatives (middle-skilled) and engineers (high-skilled) claimed that monitoring and checking pack quality and product codes (for instance via a panel or an ipad) were not tasks overly complex; in fact, companies frequently recruited external personnel to whom they administrated training in one week. By contrast, labour-use strategies of automotive plants (a typical high-cumulativeness sector) take place in a completely different technological environment. Automotive companies need close cooperation between employees of the manufacturing sites and those from product development. Such cooperation requires long and intensive vocational education, combining theoretical knowledge and practical skills. The complexity of firm organisation and production processes needs high skills and relies on incumbent workers, rather than on external personnel, recruited with temporary contracts (Krzywdzinski, 2017: 263).

To conclude, robot adoption has different impacts on job skill demands across industries. In a Peneder regime where knowledge cumulativeness is high and human capital and skills tend to be firm-specific (Malerba & Orsenigo, 1996), flexible contracts (and a higher labour turnover) are harmful as they hinder the long-run accumulation of (tacit) knowledge (Kleinknecht et al., 2014). In this case, automation benefits highly skilled workers (technicians, researchers and engineers), usually occupied in cognitive-intensive tasks, such as creativity, generalized problem solving, flexibility and complex communications (Autor et al. 2003); robotization, in particular, may favour more stable jobs such as described in Dauth et al. (2021). By contrast, in low-cumulativeness industries, automation might favour the use of flexible employment, because internal sources of knowledge are not so crucial.

Note that educational attainment and occupations may describe different aspects of the quality of labour force and they do not always overlap each other. Literature on automation and job polarisation clearly distinguishes between i) skills required for occupations (low-skilled, middle-skilled and high-skilled occupations, according to ISCO08 categories) and ii) educational attainment (OECD, 2019). Evidence on under- and over-education shows that, sometimes, the skills required do not match with the educational profile of labour supply and in cases of skill shortages, some companies resort to 'peripheral strategies such as temporary employment' (Mc

Guinness et al. 2017). In some OECD countries, a decline of middle-skilled occupations, traditionally held by full-time male workers with permanent contracts, has affected the evolution of temporary jobs, as middle-skilled occupations do not longer guarantee stable jobs and workers with secondary education have moved to low-paid/low-skilled occupations (OECD, 2019).

Building on the above considerations, we formulate our hypotheses as follows:

H.1: *In high knowledge cumulativeness industries, that mainly rely on internal knowledge sources and long-term labour relationships, robotization reduces the probability of temporary contracts for high (middle)-skilled and high (middle)-educated workers, in particular.*

H.2a: *In low knowledge cumulativeness industries, robotization may increase temporary contracts for workers endowed with high (middle)-skills or tertiary (secondary) education, if the dominant labour reallocation effect is driven by robot adopting companies that need new skills.*

H.2b: *In low knowledge cumulativeness industries, robot adoption increases temporary contracts for workers endowed with low-skills or primary education, if the dominant labour reallocation effect is driven the laggard firms that rely on cheaper and flexible labour to survive.*

Some caveats are necessary.

First, we cannot directly test either the stepping stones hypothesis or the dead-end hypothesis. We expect, however, that when in the low cum industries robots boost temporary contracts for high (middle) skilled and high (middle) educated people, it is likely that firms are using temporary contracts as a screening device and hence as a stepping stone (H.2a). Furthermore, temporary voluntary employment may be also attractive for highly productive workers who are reluctant to make large investments in a particular firm as they are not sure of their career and regional preferences (Booth et al., 2000, 2002). This may be the case for some professional workers in low cum industries, where general human capital is more important than specific human capital and highly skilled/educated workers self-select into probationary jobs. By contrast, we conjecture (H.2b) that when robotization boosts temporary contracts for low skilled and low educated people, this comes because laggard firms try to survive with flexible and cheaper labour contracts (dead end hypothesis).

To corroborate our analysis, we perform ancillary estimates to test the interplay between robots, age, and temporary jobs. In lines with previous arguments, we can state the following*:*

H.3a: *In high knowledge cumulativeness industries, robotization should reduce the probability of temporary jobs for senior workers, as the accumulation of (tacit)* knowledge from *experience is favoured by long job tenures under permanent contracts.*

H.3b: *In industries where knowledge cumulativeness is low and the dominant labour reallocation effect is driven by laggard companies that rely on cheaper labour as a survival strategy, even senior workers may have higher probabilities to get temporary contracts.*

H.3c: *If the dominant labour reallocation effect is driven by robot adopting companies that need new skills, young workers experience higher probabilities to get temporary contracts that serve as a screening device.*

Data and descriptive statistics

3.1 Data sources and variables

Three flagship databases have been merged for our empirical analysis and other secondary sources have been used to construct supplementary industry-level control variables.

First, data about individual characteristics of workers (type of contract, sex, age, wage, tenure, educational attainment, occupation) and about companies in which they are employed (firm size, industry, private versus state-owned firms) come from the *Structure of Earnings Survey (SES)*. This is a four-yearly survey, conducted by national statistical offices and coordinated by Eurostat. The *SES* collects data from enterprises with 10 and more employees. Data cover more than 1.1 million workers from our SECs and 12 industries analysed for years 2006, 2010 and 2014; they show a pooled cross-section structure[ii].

Second, information on robot adoption is from the *International Federation of Robotics* (IFR, 2016), which covers the stock of industrial robots installed over the period 1994-2014. IFR covers almost all manufacturing industries, but service sector coverage is poor. The distribution of robots across manufacturing industries is skewed, with four industries taking the lion's share, e.g., automotive, rubber and plastics, metal products and food industry (Fernandez-Macias et al., 2021, 89). The first three industries fall into Peneder's (2010) high knowledge cumulativeness group, whereas the food industry falls into the low knowledge cumulativeness category (see Table 1)[iii]. To alleviate the problem of skewness, we use a measure of variation of robot stocks over years, as discussed below.

Third, from the *EU-KLEMS* database we obtain industry level data on numbers of employees that are necessary to normalize robots at the industry-country level. In order to map IFR into SES and EUKLEMS industries we used correspondence tables (ISIC Rev.4 / NACE Rev.2) that led us to aggregate the three databases into 12 industries included in the Peneder’s taxonomy (see Table 1).

Lastly, we gather Eurostat data for trade in goods, national accounts for wage bill data, and the UN Comtrade database (only for international trade of the R&D sector); hence, following Dauth et al. (2021), we use industry-level variables measuring the variation of net exports (export – imports) over years, normalised by industry-level wage bills. This variable is expected to capture changes of temporary employment induced by trade exposure of different industries.

Our dependent variable is binary, indicating if a worker has a permanent or a temporary contract (0/1, respectively). In order to have a sharp contrast between standard and non-standard employment we excluded workers with apprenticeship contracts from our sample.

Furthermore, we have a binary explanatory variable at individual level for two age groups, i.e., older (30-64 years) versus younger workers (15-29 years). According to the International Labor Office (2013) the passage of a young person to the first stable or satisfactory job tends to occur at the age of 25-29 years. We therefore expect a negative sign for our binary variable *workers_30-64*, as seniority is expected to reduce the probability of being on a temporary job. The second important explanatory variable is about skills. We assess skills, following OECD (2019) and, after excluding agricultural and armed force occupations, we cluster the eight ISCO major groups in high-skills (managers, professionals and technicians), medium-skills (clerical support workers, craft workers, machine operators) and low-skills (service/sales workers and elementary occupations). As discussed above, education is our third, individual level, explanatory variable of interest. We draw from the SES database information about levels of highest successfully completed education and training (ISCED 2011 classification), and identify the following three categories: i) primary education (less than primary,

primary and lower secondary); ii) secondary education (upper secondary, post-secondary non tertiary); iii) tertiary education (short-cycle, master and doctoral equivalent courses).

Additional variables control for those individual characteristics that might also affect the temporary worker status, such as gender and tenure i.e., the years a worker is employed in the same company.

Robot adoption is our key explanatory variable, available at industry level. Following Acemoglu & Restrepo (2020) and Dauth et al. (2017; 2021) we measure the cumulated growth rates over ten years in robot adoption per thousand workers (employed at the initial period in a given industry) [iv].

More precisely, we calculate this variable as follows:

$$Robot\_exposure_{c,j,t1} = \frac{robots_{c,j,t1} - robots_{c,j,t0}}{Employees_{c,j,1995}} \qquad (1)$$

where c=Belgium, France, Germany, Italy, Spain and UK; j= 12 industries as reported in Table 1; t_1= 2006, 2010, 2014; t_0 = 1996, 2000; 2004.

Following Acemoglu & Restrepo (2020), we normalize the numerator of (1) by taking the employees observed in each country/industry one year *before* the base period (1995 in our case). This helps us to avoid that we normalize by employment affected by robot exposure occurring over years under scrutiny.

Obviously, for studying the effects of automation on an individual's job status, a *firm*-level measure of robot adoption would be ideal. It would allow to directly disentangle the two potential channels through which robots may fuel labour market dualization as discussed above. This is a limitation of our approach when compared to studies that use employer-employee datasets (Acemoglu et al., 2020, Dauth et al., 2021; Bessen et al., 2019; Humlum, 2019). The latter, however, concentrate on a single country. Our research has the advantage that it offers a cross-country perspective of the effects of robotization for more than 1.1 million workers by controlling for country-level differences and taking into account technological regimes.

A potential confounding factor in evaluating the impact of industry-level robot exposure on the temporary worker status could be the within-industry productivity dispersion that does not need to be driven by robots. We might observe a spurious correlation between robot adoption and the probability to have a temporary job as a result of a larger productivity dispersion across firms within the same industry. The latter may be due to major technical changes (Klepper & Miller, 1995; Klepper, 1996; Foster et al., 2018), especially those driven by process and organizational innovations supported by strong increases in intangible investments (Corrado et al., 2021) and the adoption of defensive strategies (such as cheap temporary contracts) by laggards. We follow Foster et al. (2018) and introduce the inter-quartile ratio of average wages paid by firms at country-region-industry level as a proxy for productivity dispersion.

$$Product\_disp_{c,j,r,t1} = \frac{PC75_{c,j,r,t1}}{PC25_{c,j,r,t1}} \qquad (2)$$

where *PC75* and *PC25* are the 75^{th} and 25^{th} percentiles of average wages paid at the firm level; c=Germany, Italy, Belgium, France, UK and Spain; j= 12 industries as reported in Table 1; r= NUTS1 regions; t1= 2006, 2010, 2014. The construction of $Product\_disp$ (productivity dispersion) relies on the aggregation of individual wages contained in the SES database. The availability of greater details concerning firms, industries *and* NUTS1 regions, leads us to exploit more variability for this indicator and thus to better specify $Product\_disp$ as a control variable. At the same time, creating a control variable at the industry *and* region level alleviates multicollinearity problems in regressions where we introduce other industry-level variables.

International trade could be another potential confounding factor, not necessarily captured by productivity dispersion. For example, a negative effect of intensive industry-level robot exposure on the probability to get a temporary contract may be the result of an unobserved expansion of the country-industry on international markets. Thus, a steady increase in net exports creates more stable jobs or less need of temporary contracts. To control for this aspect, we introduce an indicator of trade exposure based on Eurostat and UN Comtrade statistics.

Despite introducing these controls, we cannot exclude that other unobservable characteristics of industries simultaneously influence robot adoption and the propensity to employ temporary workers. We therefore follow Acemoglu & Restrepo (2020) and use in our sample, as instruments for industry-level robot adoption, the average robot adoption of two Asian countries that are technologically more advanced than our SECs in robotics, that is, Japan and South Korea.

Figure A.1 in the Appendix shows that the evolution of robot adoption in our six countries tracks that of Japan and Korea, although the latter is at higher levels. Therefore, we assume that technological shocks occurring in the most advanced countries in robotics will influence robot adoption in Europe, also since Japan and South Korea are important exporters of robots.

As discussed above, we also use industry-level information about a high versus a low degree of *cumulativeness of knowledge*, which we borrow from Peneder's taxonomy (2010). In the following, we assume that an innovator's ability to draw from *internally* accumulated knowledge relies on personnel with long job tenures who are able to accumulate firm-specific knowledge. Note that such knowledge tends to be weakly documented and ill-codified and is essentially 'embodied' in people. Obviously, this makes *stable* employment relations with low rates of job turnover attractive to employers. We therefore hypothesize that introduction of robots creates incentives for offering permanent rather than temporary jobs; and this incentive will be strongest in industries that rely most on accumulated knowledge. Applying Peneder's taxonomy (2010, 331) we group industries for which robot data are available in *High & Medium* versus *Low Cumulativeness* industries (henceforth: *high-cum* versus *low-cum* industries) and estimate separate equations for each group, omitting a few industries which are not covered by Peneder (2010). This strategy leads us to single out the 12 industries in Table 1.

The main interest of this study remains on the propensity to use temporary versus permanent workers in industries introducing robots. We also add some evidence about the (often poor) *quality* of temporary jobs by reporting descriptive data about hourly wages and hours worked annually. We transform hourly wages in the SES database into real wages (using 2015 Euro purchasing power parities and trimming bottom and top 1% observations to reduce the outlier problem) and estimate hours worked annually from the SES information on hours worked monthly to which the gross annual earnings relate.

3.2 Descriptive statistics

Table 1 shows summary statistics averaged over the SECs and the three SES waves (2006, 2010 and 2014) referring to about 1,1 million employees. 12 industries are clustered according to Peneder's taxonomy of knowledge cumulativeness. High-cum includes R&D services besides a number manufacturing industries, such as automotive, electrical equipment and computers, or pharmaceutical products. Within low-cum, we find public utilities (water and energy) and traditional industries such as food, textiles and footwear, wood and paper. As mentioned above (section 2.2.2), this classification is not identical with the high-tech versus low-tech classification of industries provided by Eurostat. For example, rubber and plastics, other non-metallic mineral products, basic and fabricated metal products are all medium-low tech industries according to the Eurostat classification[v], whereas they are considered high & medium knowledge cumulativeness industries within the Peneder’s taxonomy (2010). Peneder's classification has the advantage that it directly measures what we are interested in: Do innovative activities primarily use firm-specific and internal sources of knowledge, or does the firm lean more on general and externally acquired knowledge?

As expected, over the three periods (1996-2006, 2000-2010 and 2004-2014) robot exposure was, on average, more pervasive in the high-cum (5.72 robots per thousand workers) than in the low-cum industries (0.77 robots per thousand workers). Concerning trade exposure of SECs to all countries, we find that in the high-cum industries the net exports increased by 19.96 %, on average over the three periods, compared to an 0.96 % increase in low-cum industries.

Hourly wages in high-cum industries are higher than those of low-cum sectors (20.71 versus 17.73 in 2015 Euros PPP). By contrast, we did not find a significant gap in terms of annual hours of work between the two industry groups (around 2,000 hours each).

Other details on the distribution of temporary jobs are reported in Table A.1, in the Appendix. As expected, temporary workers are more frequent among younger workers and among the lowest levels of skills/education. We observe higher percentages of temporary workers in the low-cum industries. For tenure as well, the highest number of average years spent in the same firm is observed for high-skilled workers in the high-cum industries. Table A.1 also informs us about the quality of temporary jobs, approximated by the gap between temporary and permanent workers in the hourly wages and number of hours worked annually. For all categories, temporary workers always gain less compared to the permanent ones and this gap becomes particularly large for high levels of skills and education.

Interestingly, the wage gap between temporary and permanent jobs for high skilled workers is quite similar between low-cum and high-cum industries (76.82 and 77.28%, respectively). It seems therefore that there are no differences in terms of relative labour costs across the two regimes, justifying differences in temporary contracts independently of robot adoption.

It is also worth noting that skills and education do not completely overlap, especially in low-cum sectors where we find higher percentages of temporary workers and more severe temporary versus permanent wage gaps for workers with tertiary educational attainment (72.61%) compared to workers with managerial or professional occupations (76.82%). For this reason, we maintain the focus on both characteristics in the econometric analysis.

TABLE 1

4. Econometric strategy

We estimate the probability of being employed on a temporary contract applying a static probit model to the pooled sample including workers employed in our six countries over SES waves 2006, 2010 and 2014. We first explore how robot_exposure, seniority, skills and educational attainment, independently of each other, affect the probability of having a temporary job:

$$P\left(TJ_{i,c,j,r,t}=1\middle|\boldsymbol{X}_{\boldsymbol{i,c,j,r,t}}\right)=\Phi\left[\boldsymbol{X}'_{\boldsymbol{i,c,j,r,t}}\,\boldsymbol{\beta}\right]=$$

$$\Phi\begin{bmatrix}\beta_0+\ \beta_1(Rob\_exp)_{c,j,t}+\beta_2(Work\_30-64)_{i,c,j,r,t}+\boldsymbol{\beta_3}(\boldsymbol{Skills})_{i,c,j,r,t}+\\+\ \boldsymbol{\beta_4}(\boldsymbol{Education})_{i,c,j,r,t}+\beta_5(Prod\_disp)_{c,j,r,t}+\ \boldsymbol{\beta_6}(\boldsymbol{WC})_{i,c,j,r,t}+\mu_j+\zeta_r+I\end{bmatrix} \qquad (3)$$

where i= workers: 1 … 1.1 million; c= countries: 1… 6; j=industries: 1 … 12; r= NUTS1 regions: 1 … 41; and t=2006, 2010 and 2014. Unfortunately, we do not have repeated observations for the same workers; hence we deal with pooled cross sections and not panel data. The probability for workers to have a temporary contract is a function of key individual level explanatory variables, such as seniority ($Work\_30-64$), *Skills* and *Education* (low-skills and primary education being the reference groups, respectively), and the country-industry-level *robot_exposure*, that varies over 6 countries x 12 industries x 3 years (i.e., 204 observations, this is because 2006 is missing for Germany). This probability also depends on a vector *WC* of individual-level worker characteristics, such as gender and tenure, and characteristics (size and ownership) of the firm in which the individual is employed. Productivity dispersion ($Prod\_disp$) is a country-industry-region control variable as discussed above.

μ_j, ζ_r, I are respectively industry-, region- and an interaction of country- x time-specific effects taking into account all institutional differences, changes and country-level shocks that occurred between 2006 and 2014. To take account of a possible correlation of errors within workers employed in the same establishment, standard errors are clustered in all estimates at establishment level[vi].

In order to know direction and magnitude of the effects of covariates on the change of probabilities for temporary jobs, we calculate average partial effects (APEs) after each regression[vii].

In Tables 2 and 3, our estimated models introduce interaction terms to analyse whether *robot_exposure* moderates the relationship between seniority/education/skills and temporary jobs:

$$P(TJ_{i,c,j,r,t} = 1 | \boldsymbol{X_{i,c,j,r,t}}) = \Phi[\boldsymbol{X'_{i,c,j,r,t}}\,\boldsymbol{\beta}] =$$

$$\Phi\begin{bmatrix} \beta_0 + \beta_1(Rob\_exp)_{c,j,t} + \boldsymbol{\beta}_2(\boldsymbol{ME})_{i,c,j,r,t} + \beta_3\left(Rob_{\exp *Work}\_30-64\right)_{i,c,j,r,t} + \boldsymbol{\beta_4}\left(Rob_{\exp *\boldsymbol{Skills}}\right)_{i,c,j,r,t} + \\ +\boldsymbol{\beta_5}(Rob\_\exp * \boldsymbol{Educ})_{i,c,j,r,t} + \beta_6(Prod\_disp)_{c,j,r,t} + \boldsymbol{\beta_7}(\boldsymbol{WC})_{i,c,j,r,t} + \mu_j + \zeta_r + I \end{bmatrix} \quad (4)$$

where now ME is a vector including main effects for $Work\_30-64$, *Skills* and *Education*.

We run estimates of models 3 and 4 or the total sample and separately for high and low knowledge cumulativeness industries (high-cum and low-cum, respectively). As hypothesized above, we expect Rob_exp to have a different impact between knowledge cumulativeness regimes and coefficients for the *total* sample can mask heterogeneity.

As we discussed in the previous section, if *robot exposure* is endogenous the coefficients of interest β_1, β_3, $\beta_4$and β_5, in equation 4, could be biased. For this reason, we perform an instrumental variable probit regression based on the control function approach (CF). According to Wooldridge (2010; 2015), this method needs fewer assumptions and is computationally simpler than Maximum Likelihood.

The control function method follows a two-step procedure (Wooldridge 2015). In the first step, the regression of the endogenous variable contains all exogenous variables, including instruments (average robot exposure of Japan and Korea and its interacted term). In the second step, to eliminate endogeneity, the residuals obtained from the first stage are included in the original equations (equations 3 and 4, in our study). This approach allows us to isolate the changes in exposure driven by technological progress, and, at the same time, remove occupation-specific shocks that affect robot adoption and the probability of transition out or into temporary occupation.

Since our endogenous variables of interest are continuous, we perform in the first stage an OLS regression of these endogenous variables (Rob_exp and its interactions with $Work\_30-64$, *Skills* and *Education*) on instruments and other exogenous variables as follows:

$$(Rob\_exp * WS)_{i,c,j,r,t} = \beta_0 + \beta_1(Rob\_exp\_Jp\_Kr * WS)_{j,c,j,r,t} + \beta_2(Prod\_disp)_{i,c,j,r,t} + \boldsymbol{\beta_3}(\boldsymbol{WC})_{i,c,j,r,t} + \zeta_r + I + \upsilon_{i,c,j,r,t} \quad (5)$$

where $Rob\_exp * WS$ is, alternatively, the interaction with either $Work\_30 - 64$ or *Skills/Education* (Medium and High-skills; Secondary and Tertiary Education); $Rob\_exp\_Jp\_Kr * WS$ is the interaction of the same variables with the average *robot_exposure* of Japan and South Korea. The remainder includes the exogenous variables of the structural equation 4. In doing so, we follow Wooldridge (2010, 592-593) and assume that instruments that are good for *robot exposure*, are also good for the interaction terms. Of course, we also replicate equation 5 for the main effects only, that is Rob_exp as endogenous dependent variable and $Rob\_exp\_Jp\_Kr$ as instrument.

In the second stage, as mentioned above, we run a probit regression similar to equation 4, in which we add residuals from the first stage. The statistical significance of residuals means that the variables of interest (Rob_exp and its interacted terms) are truly endogenous and give us feedback about the helpfulness of the CF approach (see Tables 3 and A.2-A.4 in the Appendix). Since variables generated in the first stage (residuals) are introduced in the second stage, this IV two stages approach needs appropriate correction of standard errors by means of a bootstrap procedure (Wooldridge, 2015). The results for the first stage of CF estimation and tests about the relevance of our instruments (the Kleinbergen-Paap Wald F statistic is used for the weak identification test, see Baum et al., 2007) are reported in the Appendix (Tables A.5-A.8).

An important variable to consider is international trade. Indeed, the assumed exogenous shock that robot implementation in Japan-Korea induces robot implementation in Europe may be confounded by exposure to trade (Acemoglu and Restrepo, 2020; Dauth et al., 2021). For example, an increase of robot implementation in our six countries may be the result of increasing net exports rather than the technological shock propagating from the Asian countries. Likewise, in the second stage estimation, changes in trade patterns could be responsible for higher or lower propensities to employ temporary workers independent of robot adoption, as already discussed above. As a robustness check, we introduce (see Tables A.3 and A.4 in the Appendix), two industry-level control variables that approximate the industry-specific trade exposure of our sampled countries to all countries (*Trade_exposure _World*) or to Japan and South Korea only (*Trade_exposure_Japan_Korea*).

As an additional robustness check, we exclude Spain, the country that has exceptionally high shares of temporary workers, as shown by Figure 2 (see the estimates reported in Table A.5 in the Appendix).

Eventually, we follow Greene (2010) and provide a graphical representation of APEs that were statistically significant in Table 3, to correctly interpret the interaction terms in a probit model. More in detail, we calculate predicted probabilities for temporary jobs, and show their discrete changes. Figures 3 and 4 illustrate the predicted probabilities to get a temporary contract detailed by country, over low-cum versus high-cum industries and separately by skills (Fig. 3) and by education levels (Fig. 4). These probabilities have been estimated over increasing values of robot exposure measured at the 10^{th} (pc_10), the median (pc_50) and 90^{th} (pc_90) percentiles, whereas all other covariates have been taken at their means.

Figure 5 gives the same information detailed by years (2006, 2010, 2014) for the total of our SECs.

5. Econometric Results

5.1 Robots, seniority, skills, education and temporary jobs: probit and IV probit (Control Function approach)

Both probit and IV probit models share the same estimation strategy. We first study the main effect of *Robot exposure* (equation 3) and only control for *country x time-specific* effects (column 1), in order to take into account all labour market institutional changes, while we allow variability and idiosyncratic factors at the industry-level to play a role. Next (columns 2-10), we introduce industry specific effects, use interactions between robots and worker seniority/skills/education and run regressions over the total sample and separately for low-cum and high-cum industries.

Our baseline probit estimation, reported in Table 2, serves as a benchmark, besides being useful to detect specification and goodness of fit of the overall model. The percentage of correctly specified observations is always around 95% and signals quite a high association between actual and fitted values (Cameron & Trivedi, 2009).

All coefficients reported are APEs. Control variables are in line with empirical studies on determinants of temporary employment (Eurofound, 2015). As expected, longer tenure, *age 30_64*, higher skills and/or education as stand-alone terms reduce the probability of being a temporary worker. In other words, people in the reference group (younger, low-skilled/low-educated workers, or workers with short job tenures) have a higher chance of being on temporary jobs. In line with Eurofound (2015, 25), we find that being a woman has little impact on the probability to be a temporary worker in most specifications reported in Table 2. As expected, productivity dispersion (that also controls for potential asymmetric introduction of process and organizational innovations among firms within the same industry/region) positively affects the propensity to employ temporary workers in the total sample. One unit change in the interquartile ratio (that exactly ranges from 1 to 2 in our sample) increases the probability of temporary contracts by 0.003.

This fairly small effect may be the result of opposite impacts in high-cum versus low-cum industries. In low-cum industries, productivity dispersion may trigger labour reallocation and induce an *increase* of temporary employment as these industries lean more on external rather than on internally developed knowledge, making cheap temporary contracts more attractive. By contrast, in high-cum industries a greater productivity dispersion induces a reduction of flexible contracts because internal knowledge sources are more important than externally acquired knowledge, making it more difficult for all enterprises (leaders and low performers) relying on labour flexibility.

For *Robot exposure* and its interactions, we obtain the expected opposite effects between low- and high-cum industries when we turn to the mediating effects of robot exposure on the relationships between different skills/education and the probability to have temporary jobs. However, as these findings could be affected by the endogeneity of *Robot exposure*, we postpone a more detailed discussion of our results to the IV CF probit model, reported in Table 3. Here, only APEs of our key explanatory variables have been shown (robot exposure and its interaction with age, skills and education), whereas coefficients for all other control variables, already used in Table 2, are available upon request.

TABLE 2

TABLE 3

Compared to our baseline model in Table 2, the estimates of the IV CF probit model (Table 3) change only little, apart from losing the already low statistical significance of seniority (Table 3, columns 2-4), while the magnitude and statistical significance of the coefficients associated to Robot exposure and its interactions with skills and education are greater (Table 3, columns 5-10). One should note that the significant coefficient of residuals (Table 3) and the first stage results reported in the Appendix (Table A.5) show that controlling for endogeneity through the IV CF probit model is necessary (at least where robot exposure shows statistical significance). We find that the average of robot exposure of Japan and South Korea (Rob_exp_Jp_Kr) is a relevant instrument, as it is correlated with the endogenous variable (*Robot_exposure*) and the F statistics is always above the critical value (bottom of Table A.5).

In Table 3 (as in Table 2) *Robot exposure* as a stand-alone explanatory variable (column 1) reduces the probability for temporary jobs when we control for country-level unobserved heterogeneity (i.e., institutional differences and changes), while allowing for between-industry variability. More in detail, on average in the total sample, robots increased by 4.19 units per thousand workers, with a standard deviation of about 10 (see Table 1). If we assume the standard deviation of ten robots per thousand workers as a plausible change in our sample, we obtain (column 1) that an increase of ten robots significantly reduces the probability to get a temporary job by 0.03 (3 percentage points).

Next, to test our above hypotheses we study the effect of *Robot_exposure* across different categories of employees (younger/senior, high/med-/low-skilled or educated workers) and split the sample in low- and high-cum industries to understand the role played by these two knowledge cumulativeness regimes. The inclusion of sector dummies allows us to correct for heterogeneity across industries (Table 3, columns 2-10).

First, we observe that the influence on differently skilled/educated workers, shown in the probit model of Table 2, is confirmed when we correct for endogeneity (Table 3, columns 5-10).

In more detail, in the whole sample (Table 3, columns 5 and 8) we find that an increase by ten robots per thousand workers significantly reduces the probability of temporary jobs only for highly skilled and highly educated workers by 0.01 and 0.02 (1 and 2 percentage points), respectively. These results are confirmed in high-cum industries (Table 3, columns 7 and 10)[viii], while the opposite results emerge in the low-cum ones, where *Robot_exposure*, measured as ten robots increase per thousand workers, positively affects the probability of flexible contracts for both medium and high-skilled/educated workers by 2 and 1 percentage points, respectively (Table 3, columns 6 and 9). To detect the statistical significance of low-cum vs high-cum differences in the APEs reported above, we follow the approach proposed by Mize et al. (2019) and find confirmation that they are all significantly different from zero (see column 3, Table A.9 in the Appendix and the note at the bottom for more details).

From Table 3, we can also see that the interaction term *Robots x Workers_30-64* is always insignificant (columns 2-4), meaning that robot adoption seems to play *no* role for employing younger (or older) people as temporary workers. It means that the probability for older people to be in a temporary labour status are lower than that of younger workers (see the coefficients for *Work_30-64* in Table 2, columns 2-4), but robots do not affect this outcome.

Overall, these results inform us about a partial relevance of our hypotheses.

As expected, (H.1), in high-cum industries, robot adoption reduces the probability to get temporary jobs for high-skilled/educated workers (columns 7 and 10). For medium skilled workers, the estimate is not significant, while for medium education we obtain a non-robust result, as the total effect is slightly positive in Table 3 (column 10) and slightly negative when we perform robustness checks (Tables A.2, A.3, A.4, column 10)[ix].

For low-cum industries, our findings seem to support H.2a instead of H.2b, i.e., companies introducing robots (and not the laggards) are the drivers of increases of temporary employment (see columns 6 and 9). This is because companies in low-cum industries need higher levels of education and skills to employ workers with fixed-term contracts and they can adopt this recruitment strategy because they have lower constraints in terms of firm-specific skills. Also note, that in low-cum industries there are no polarization effects, since the estimated effects for medium skilled/educated workers do not differ from those obtained for high skilled/educated ones (which is consistent with findings by Graetz and Michaels, 2018)[x].

It is also noteworthy, especially for high-skilled workers, that the gap in terms of hourly wages between temporary and permanent workers is similar across technological regimes, 76.82% versus 77.28% in low-and high-cum industries respectively, as discussed in section 3.2 (see Table A.1 in the Appendix). Thus, we conjecture that the higher propensity to employ temporary and better skilled workers in low-cum industries (with respect to high-cum ones) is not simply due to lower relative labour costs (76.82%) compared to relative costs in high-cum industries (77.28%), but probably relies on easier absorption of external source of knowledge to adapt robots to their organisations. We see therefore an interesting parallel with earlier research: numerically flexible labour is a disadvantage for innovation and productivity in high-cum, but not necessarily in low-cum industries (Pieroni & Pompei, 2007; Kleinknecht et al., 2014; Kleinknecht, 2020; Wachsen & Blind 2016; Vergeer et al. 2015).

Differently from single-country studies such as that of Cuccu and Royuela (2022) that only focuses on Spain, we do not find any significant effect of intensive robotization on the probability to get temporary jobs for low-skilled workers. As for high-cum industries, this can be explained by a likely displacement effect of low skilled/educated workers performing routinary tasks, and an increasing difficulty to be re-employed by means of temporary contracts in environments where the complex organisation of companies requires personnel with knowledge and experience accumulated within the firm. In the low-cum industries, instead, where it is easier to recruit external personnel with general knowledge, a composition effect is at work. While we observe the dominant mechanism where high skilled workers are recruited through temporary contracts (H.2a), we cannot exclude that non adopters of robots employ low skilled workers as strategy to reduce costs and survive the market (H.2b). Unfortunately, the limitations of our database (lack of employer-employee matched information) do not allow to disentangle such effects.

Further, we can say nothing about the mediating effect of robots on age and probability to get temporary jobs, as neither H.3a nor H.3b and nor H3c have been confirmed. While we expected from the literature discussed above some complementarities between skills/education and age profiles, our analysis tells us that robot adoption does not specifically affect the overall pattern, where employees aged 30-64 have lower probabilities to fall in the temporary worker status.

5.2 Robots, seniority, skills, education and temporary jobs: robustness checks

As already discussed in sections 3 and 4, at least two concerns related to results of Table 3 merit attention. First, changes in the trade patterns across industry-countries may not be captured by industry dummies and may interfere both in the relationship between European robot adoption and temporary employment, and in the relationship between Asian and European robot exposure, that is the first stage of our IV CF probit model.

Table A.2 in the Appendix shows what happens to outcomes of Table 3 when we introduce a variable that captures changes over time of net exports of our six countries to all partner countries around the world. We obtain that an increase of net exports slightly reduces the probability to hire temporary workers (Table A.2, column 1), whereas the coefficient of robot exposure remains significant and not altered, as shown by the comparison with Table 3. As expected, a long-term expansion on international markets probably yields a productivity effect by reducing the demand for low quality temporary jobs. Although this control for trade becomes rarely significant in the specifications with the interaction terms, the pattern we obtained from Table 3 is substantially confirmed (Table A.2, columns 2-10). The first stage of the model, presented in Table A.2, shows that changes in trade do not even interfere with the correlation between the Japan-Korea robot exposure and that occurring in our six European countries, as all coefficients remain highly significant with the expected sign (see Table A.6 in the Appendix).

Things change little when we use a more specific control for trade, measured by changes of net exports of our six countries to Japan and South Korea (see Table A.3 for main results and Table A.7 for first stage results).

Finally, we should examine whether the exceptional values of temporary workers in Spain (Figure 2) have an impact on results in Table 3. We ran again the same regressions, but omitting Spain. The exclusion of Spain causes little difference, except for making the positive coefficient for low-educated workers in high-cum industries insignificant and turning significant negative coefficients for both younger and older workers in the high-cum sectors as well (see Tables A.4 for main results and Table A.8 for first stage results in the appendix)[xi]. This reinforces our main expectations concerning the lower attractiveness of using temporary employment in high-cum industries when robot exposure intensifies.

On the other hand, these latter results lead us to better understand to what extent heterogeneity across countries and changes over the three years under scrutiny (that include the 2008-2009 Great Recession) may have conditioned the overall results of Table 3.

5.3 Robots, seniority, skills, education and temporary jobs across countries and over years

As reported in section 4, the average partial effects, discussed so far, often need a graphical representation to interpret correctly the interaction effects (Greene, 2010). Further, we cannot be sure to what extent our results of Table 3 are not conditioned by influential values concentrating in some specific country or year.

Figures 3 and 4 report graphical representations of models with interactions depicted in Table 3 across our six countries, while Figure 5 represents the same interactions over the three years included in our sample (2006, 2010, 2014).

In particular, the interaction of robot-exposure with skills is reported in Figure 3, where the predicted probabilities to get a temporary contract for each category of skills have been estimated over increasing values of robot exposure measured for each specific country at the 10^{th} (pc_10), the median (pc_50) and 90^{th} (pc_90) percentiles. In four out of six countries (Belgium, France, Germany and Italy) the results are consistent with the APEs observed in Table 3. Indeed, if we focus on low-cum industries the positive interaction effect is visible through a narrowing gap between the predicted probabilities for high-skilled (medium-skilled) workers and those of low-skilled workers as robot exposure increases (Figure 3 Panel A). The opposite holds in the high-cum industries, where a significant reduction of probabilities to get temporary jobs is only experienced by high-skilled workers (see Table 3); indeed, we observe a widening gap between predicted probabilities of this group of workers and the rest of employees in Figure 3 (Panel B).

In line with APEs found for interactions with education (see Table 3, columns 9 and 10), we observe in Figure 4 a pattern very similar to that illustrated in Figure 3.

Eventually, the aggregate picture of our sample for different years is presented in Figure 5. The pattern described by APEs in Table 3 seems particularly evident during the post-crisis years (2010 and 2014).

FIGURE 3

FIGURE 4

FIGURE 5

6 Conclusions

The persistent labor market duality fueled by a segment of temporary and often 'dead-end' jobs, associated with risks of becoming 'working poor', raises concerns among the public and among policy makers across Europe (European Commission, 2020). We explore links between individual-level probabilities of workers to get a temporary contract and the last wave of robotization that occurred in six European countries.

We first analyze if the industry-level robot exposure changes the usual pattern where young, low skilled and low educated workers typically have high probabilities falling into a temporary worker status. Second, we investigate whether effects of robots along the age, skills and education profiles of workers are different, depending on the Schumpeterian innovation regime dominant in an industry. The latter indeed makes a decisive difference. We made use of the taxonomy of industries by Peneder (2010) who distinguished industries by their dominant innovation model according to 'cumulativeness of knowledge'. We find that only in highly robot-adopting industries with a *high* cumulativeness of knowledge, high-skilled and highly educated people have lower probabilities of getting temporary jobs, compared to their medium- and low-skilled peers. By contrast, in *low* knowledge cumulativeness industries, workers with higher skills and (tertiary) education are more likely to be in temporary jobs.

These findings contribute to understanding the increasing shares in Europe of temporary workers with tertiary education and occupied as technicians and professionals as observed by Eurofound (2015 and 2020). We interpret this result as an indication that the dominant effect in these industries is driven by robot adopting firms that need external skills to manage their automatized production processes and hiring on temporary jobs is easier to do if knowledge cumulativeness is low. In this case they might use temporary contracts as a screening device to find the right person.

Of course, this conjecture would be supported if we found in the low knowledge cumulativeness industries that younger people were experiencing even higher probabilities of temporary hiring, than that they usually have in the total economy. This would have backed the idea that the screening device is especially applied for young and highly educated people and temporary contracts may serve as stepping stone to highly paid and more secure jobs. Instead, we found that robot adoption does not influence any of these probabilities along the age profile of workers.

It remains, therefore, an open question whether these temporary jobs will function as screening devices or rather as dead-end jobs. Our incapacity to answer this question is mainly due to data limitations. Indeed, more research is needed, using employer-employee linked data combined with firm-level information about robot adoption and a panel structure, which is not in our database. If such data were available, we could better disentangle the impact of robotization on the creation of 'good' versus 'bad' jobs in both innovation regimes.

Further heterogeneities that could be interesting to explore are the role of national regulations of labour markets and their mutual interactions. The main effects of temporary jobs can be different across countries because of the interactions of employment protection legislation with other labour institutions, for example, the regulations that involve firm-provided training, as the apprenticeship. Paradoxically, in OECD countries, workers whose jobs are at higher risk of automation less likely are engaged in learning (OECD, 2019, ch. 6). A better understanding of the specific barriers faced by the most vulnerable groups and further explorations of policy interactions may provide useful information to adopt the better strategies to deal with the innovation employment nexus.

We conclude that, in *low* cumulativeness industries, the main result might be based on a dominant effect where high rates of robot adoption boost temporary contracts among highly skilled and highly educated workers. However, the opposite force based on a large population of non-adopters of robots resorting to labour flexibility as a survival strategy, independently of the quality of human resources, is not negligible. Our descriptive statistics on lower hourly wages paid to temporary workers corroborate this claim and shed light on the risk of a 'discontinued career made up of a repetition of short-term and low paid jobs' (Filomena and Picchio 2022, 62).

Our results also carry a suggestion with respect to the studies mentioned in our literature survey. These studies tend to report ambiguous outcomes, and, often, the effects found are not so big. Given that, for some key variables, we find opposite signs of coefficients in low-cum versus high-cum industries, it might be rewarding if the various models were re-estimated, including controls for the dominant innovation model in an industry. Rather than using 'blind' sector dummies, one should include 'informed' sector dummies from the painstaking work by Peneder (2010), which may shed new light on the impact of robotization on employment.

References

Acemoglu, D., Lelarge, C., & Restrepo, P. (2020). Competing with robots: Firm-level evidence from France. *AEA Papers and Proceedings,* 110 (May): 383-88.

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: how technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2): 3-30.

Acemoglu, D. & Restrepo, P. (2020). Robots and jobs: Evidence from US Labor Markets. *Journal of Political Economy, 128*(6):2188-2244.

Andrews, D, Criscuolo, C. & Gal P.N. (2015) Frontier firms, technology diffusion and public policy, OECD Working Papers 2015-12, Paris: OECD.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4): 1279-1333.

Baum, C. F., Schaffer, M. E., & Stillman, S. (2007). Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *The Stata Journal*, *7*(4): 465-506.

Bessen, J. E., Goos, M., Salomons, A., & Van den Berge, W. (2019). Automatic Reaction-What Happens to Workers at Firms that Automate? Boston Univ. School of Law, Law and Economics Research Paper.

Blanchard, O., & Landier, A. (2002). The perverse effects of partial labour market reform: fixed-term contracts in France. *The Economic Journal*, 112(480): F214-F244.

Boeri, T. (2011). 'Institutional reforms and dualism in European labor markets', in (O. Ashenfelter and D. Card, eds.), *Handbook of Labor Economics*:1173–236, Amsterdam and New York: Elsevier.

Booth, A. L., Francesconi, M., & Frank, J. (2000). Temporary jobs: Who gets them, what are they worth, and do they lead anywhere? (No. 2000-13). ISER Working Paper Series.

Booth, A. L., Francesconi, M., & Frank, J. (2002). Temporary jobs: stepping stones or dead ends?. *The Economic Journal*, 112(480): F189-F213.

Breschi, S., Malerba, F. & Orsenigo, L. (2000). Technological regimes and Schumpeterian patterns of innovation, *The Economic Journal*, 110 (463): 288–410.

Cameron, A. C., & Trivedi, P. K. (2009). *Microeconometrics using stata*, *2*(5): 706, College Station, TX: Stata press.

Cappellari, L., Dell'Aringa, C., & Leonardi, M. (2012). Temporary employment, job flows and productivity: A tale of two reforms. *The Economic Journal*, 122(562): F188-F215.

Cetrulo, A., Cirillo, V., & Guarascio, D. (2019). Weaker jobs, weaker innovation. Exploring the effects of temporary employment on new products. *Applied Economics*, 51(59): 6350-6375.

Corrado, C., Criscuolo, C., Haskel, J., Himbert, A., & Jona-Lasinio, C. (2021). New evidence on intangibles, diffusion and productivity. OECD Science, Technology and Industry Working Papers 2021/10, OECD Publishing, Paris.

Cuccu, L., & Royuela, V. (2022). Just reallocated? Robots, displacement and job quality. Mimeo.

Dauth, W., S. Findeisen, J. Südekum, & N. Woessner (2017) 'German robots-the impact of industrial robots on workers' CEPR Discussion Paper No. DP12306.

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6): 3104–3153.

Destefano, T., Haneda, S., & Kwon, H. U. (2019). Determinants of Structural Adjustment and Employment Use in Japan: Firm Characteristics, Offshoring and Industrial Robotics. RIETI.

Dixon, J., Hong, B., & Wu, L. (2021). The robot revolution: Managerial and employment consequences for firms. Management Science, /doi.org/10.1287/mnsc.2020.3812.

Dosi, G. (2008). Statistical regularities in the evolution of industries. A guide through some evidence and challenges for the theory, in Malerba F. & Brusoni S. (Eds.) *Perspectives on Innovation*, Cambridge, Cambridge University Press.

Dosi, G., Piva, M., Virgillito, M. E., & Vivarelli, M. (2021a). Embodied and disembodied technological change: The sectoral patterns of job-creation and job-destruction. *Research Policy*, 50(4): 104199.

Dosi, G., Guarascio, D., Ricci, A., & Virgillito, M. E. (2021b). Neodualism in the Italian business firms: training, organizational capabilities, and productivity distributions. *Small Business Economics*, 57(1): 167-189.

Eurofound (2015). Recent developments in temporary employment: Employment growth, wages and transitions, Publications Office of the European Union, Luxembourg.

Eurofound (2020), Labour market change: Trends and policy approaches towards flexibilisation, Challenges and prospects in the EU series, Publications Office of the European Union, Luxembourg.

European Commission (2020), Joint Employment Report 2020, European Commission Directorate-General for Employment, Social Affairs and Inclusion. 1049 Brussels.

Fernandez-Macias, E., Klenert, D., & Anton, J. I. (2021). Not so disruptive yet? Characteristics, distribution and determinants of robots in Europe. *Structural Change and Economic Dynamics*, *58*: 76-89.

Filomena, M. & Picchio, M. (2022). Are temporary jobs stepping stones or dead ends? A systematic review of the literature. *International Journal of Manpower*, 43(9): 60-74

Foster, L., Grim, C., Haltiwanger, J. C., & Wolf, Z. (2018). *Innovation, productivity dispersion, and productivity growth*. National Bureau of Economic Research. n. 24420.

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5): 753-768.

Greene, W. (2010). Testing hypotheses about interaction terms in nonlinear models. *Economic Letters* 107(2): 291–296.

Humlum, A. (2019). Robot adoption and labor market dynamics. Princeton University.

International Federation of Robotics (2016) 'World Robotics Industrial Robots 2016' International Federation of Robotics, https://ifr.org/img/office/Industrial_Robots_2016_Chapter_1_2.pdf.

International Labour Office (2013). *Global employment trends for youth 2013: A generation at risk*. Geneva: International Labour Office.

Kleinknecht, A. (2020). The (negative) impact of supply-side labour market reforms on productivity: an overview of the evidence. *Cambridge Journal of Economics*, 44(2): 445-464.

Kleinknecht, A., van Schaik, F. N., & Zhou, H. (2014). Is flexible labour good for innovation? Evidence from firm-level data. *Cambridge journal of economics*, *38*(5): 1207-1219.

Klepper, S. (1996). Entry, exit, growth, and innovation over the product life cycle. *The American Economic Review*, 86(3): 562-583.

Klepper, S., & Miller, J. H. (1995). Entry, exit, and shakeouts in the United States in new manufactured products. *International Journal of Industrial Organization*, *13*(4): 567-591.

Koch, M., Manuylov, I., & Smolka, M. (2021). Robots and firms, *Economic Journal*, 131(638): 2553-2584.

Krzywdzinski, M. (2017). Automation, skill requirements and labour use strategies: high-wage and low-wage approaches to high-tech manufacturing in the automotive industry. *New Technology, Work and Employment*, 32(3): 247-267.

Lloyd, C., & Payne, J. (2021). Fewer jobs, better jobs? An international comparative study of robots and ‘routine’work in the public sector. *Industrial Relations Journal*, 52(2): 109-124.

Malerba, F., & Orsenigo, L. (1996). Schumpeterian patterns of innovation are technology-specific. *Research Policy*, 258(3):451-478.

McGuinness, S., Pouliakas, K., & Redmond, P. (2017). How useful is the concept of skills mismatch? IZA Discussion Papers No.10786.

Mize, T. D., Doan, L., & Long, J. S. (2019). A general framework for comparing predictions and marginal effects across models. *Sociological Methodology*, 49(1): 152-189.

OECD (2019). OECD employment outlook 2019: The future of work. OECD Publishing, Paris.

Peneder, M. (2010). Technological regimes and the variety of innovation behaviour: Creating integrated taxonomies of firms and sectors. *Research Policy*, *39*(3):323-334.

Pieroni, L., & Pompei, F. (2007). Evaluating innovation and labour market relationships: the case of Italy. *Cambridge Journal of Economics*, 32(2):325-347.

Vergeer, R., Kraan, K., Dhondt, S., Kleinknecht, A. (2015). Will 'structural reforms' of labour markets reduce productivity growth? A firm-level investigation, *European Journal of Economics and Economic Policy*, 12(3): 300-317.

Wachsen, E., & Blind, K. (2016). More labour market flexibility for more innovation? Evidence from employer–employee linked micro data. *Research Policy*, 45(5): 941-950.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, 50(2): 420-445.

TABLES AND FIGURES

TABLES

Table 1: Summary statistics for variables used in the empirical analysis

Variables	Total Mean	Total *sd*	*Hi-Cum* Mean	*Hi-Cum* *sd*	*Low-Cum* Mean	*Low-Cum* *sd*
SES dummy/categorical variables (individual-level)						
Temporary Workers (share)	7.27	(25.97)	7.23	*(25.70)*	7.30	*(25.86)*
Workers_30-64	84.30	(36.38)	83.72	*(36.92)*	85.63	*(35.08)*
Public ownership	8.42	(27.77)	5.75	*(23.28)*	13.70	*(34.38)*
Women	29.68	(45.68)	28.49	*(45.13)*	32.41	*(46.80)*
Prim_Education	22.71	(41.90)	19.59	*(39.69)*	31.24	*(46.35)*
Sec_Education	57.92	(49.37)	58.13	*(49.33)*	56.88	*(49.52)*
Tert_Education	19.37	(39.52)	22.28	*(41.61)*	11.88	*(32.36)*
Low -Skilled	11.20	(31.54)	8.42	*(27.76)*	17.19	*(37.73)*
Middle-Skilled	53.68	(49.86)	52.42	*(49.94)*	58.22	*(49.32)*
Hi-Skilled	35.12	(47.73)	39.16	*(48.81)*	24.60	*(43.07)*
Small Firms	22.81	(41.96)	22.26	*(41.60)*	24.59	*(43.06)*
Medium_Sized Firms	30.58	(46.08)	29.04	*(45.40)*	33.75	*(47.29)*
Large Firms	46.61	(49.88)	48.69	*(49.98)*	41.66	*(49.30)*
SES continuous variables (individual- and region-industry level)						
Tenure	11.02	(10.41)	13.73	*(12.86)*	10.85	*(10.39)*
Product_disp	1.44	(0.13)	1.42	*(0.14)*	1.55	*(0.24)*
Hourly Wages	19.75	(9.65)	20.71	*(10.08)*	17.73	*(8.31)*
Yearly hours worked (.000)	2.03	*(0.48)*	2.02	*(0.48)*	2.03	*(0.48)*
IFR & Eurostat continuous variables (industry-level)						
Robot_exposure	4.19	*(10.26)*	5.72	*(11.91)*	0.77	*(2.56)*
Trade_exposure World	8.13	*(96.70)*	19.98	*(157.08)*	0.96	*(8.41)*
Trade_exposure Japan_S.Korea	4.20	*(44.66)*	-0.20	*(4.24)*	6.78	*(56.07)*
Observations	*1,137,288*		*769,352*		*367,936*	

Industries	***Hi-Cum***	***Low-Cum***
	1)Petroleum, Chem. & Pharma 2)Rubber, Plastic & Non- Metallic 3)Metal Products 4)Machinery 5)Motor vehicles & Transport Eqmt. 6)Electrical Eqmt & Computers 7)R&D	1)Mining & Quarrying 2)Food Industry 3)Textile & Garments 4)Wood &Printing 5) Public Utilities

Source: SES_2006, 2010 and 2014, Eurostat; IFR and EUKLEMS. Note: All values are percentages with exception for Tenure (the length of service in the same enterprise is measured in years), Robot-exposure (Δrobots x thousand workers); Product_disp (ratio $75^{th}/25^{th}$ percentiles of average wages at firm-level); wages (real hourly wages in 2015 Euros PPP) and number of hours worked annually. Total corresponds to the whole sample (12 industries)that is the sum of Hi-Cum and *Low-Cum industries according to the Peneder's taxonomy.*

Tab 2 Probability to get a temporary job and robot exposure by seniority, skills and education of workers (**Baseline Probit Model**, average partial effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Rob_exp x Work_30-64			**Rob_exp x Skills**			**Rob_exp x Education**		
	Total	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum
Rob_exposure	-0.0002***	0.000	-0.001**	0.000	0.000	-0.001	0.000	0.0002**	0.000	0.0003***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Robots x Work_30-64		0.000	0.002***	0.000						
		(0.000)	(0.000)	(0.000)						
Rob x Med_skilled					0.000	0.001***	0.000			
					(0.000)	(0.000)	(0.000)			
Rob x High_skilled					-0.0004***	0.001**	-0.001***			
					(0.000)	(0.001)	(0.000)			
Rob x Sec_Educ								-0.0001**	0.000	0.000
								(0.000)	(0.000)	(0.000)
Rob x Tert_Educ								-0.001***	0.001	-0.001***
								(0.000)	(0.001)	(0.000)
Work_30-64	-0.026***	-0.026***	-0.026***	-0.026***	-0.027***	-0.026***	-0.023***	-0.027***	-0.026***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Med_skilled	-0.001	-0.002	0.001	-0.004**	-0.003**	0.000	-0.005***	-0.002*	0.001	-0.004**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
High_skilled	-0.011***	-0.011***	-0.007***	-0.014***	-0.010***	-0.006***	-0.016***	-0.011***	-0.007***	-0.014***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Secondary Education	-0.010***	-0.011***	-0.013***	-0.007***	-0.010***	-0.012***	-0.007***	-0.010***	-0.011***	-0.008***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tertiary Education	-0.010***	-0.010***	-0.011***	-0.015***	-0.010***	-0.011***	-0.015***	-0.008***	-0.008***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Product_disp	0.031***	-0.003	0.030***	-0.028***	-0.003	0.029***	-0.028***	-0.003	0.028***	-0.028***
	(0.004)	(0.005)	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)	(0.005)	(0.007)	(0.008)
Public	0.046***	0.045***	0.005**	0.062***	0.044***	0.005**	0.062***	0.044***	0.005**	0.062***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Tenure	-0.038***	-0.037***	-0.037***	-0.036***	-0.037***	-0.037***	-0.036***	-0.037***	-0.037***	-0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Women	0.000	-0.001*	-0.001*	0.000	-0.001	-0.001	0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Medium Sized Firms	0.014***	0.013***	0.008***	0.014***	0.013***	0.008***	0.014***	0.013***	0.008***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Large Firms	0.025***	0.026***	0.020***	0.025***	0.026***	0.020***	0.026***	0.026***	0.020***	0.026***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,137,288	1,137,288	367,936	769,352	1,137,288	367,936	769,352	1,137,288	367,936	769,352
Pseudo_R2	0.25	0.26	0.26	0.28	0.26	0.26	0.27	0.26	0.26	0.28
% correctly classified	95.79	95.84	96.14	95.71	95.84	96.13	95.71	95.84	96.12	95.72

*Note: Establishment level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Pseudo_R2 and % correctly classified observations measure the goodness of fit. Robot-exposure is a country-industry level variable calculated as cumulative change of number of industrial robots over periods 1996-2006; 2000-2010 and 2004-2014 on country-industry level employees in 1995. All other variables refer to years 2006, 2010, 2014. Product_disp is a proxy for productivity dispersion at country-industry-region level, that is, the interquartile ratio of firm level average wages. The dependent variable and all other regressors are worker level variables. Primary Education is the omitted variable for education; Low-Skilled is the omitted variable for Skills, Small Firms is the omitted variable for firm size. Total corresponds to the whole sample (12 industries), that is in turn composed by Hi-Cum* and *Low-Cum industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1.*

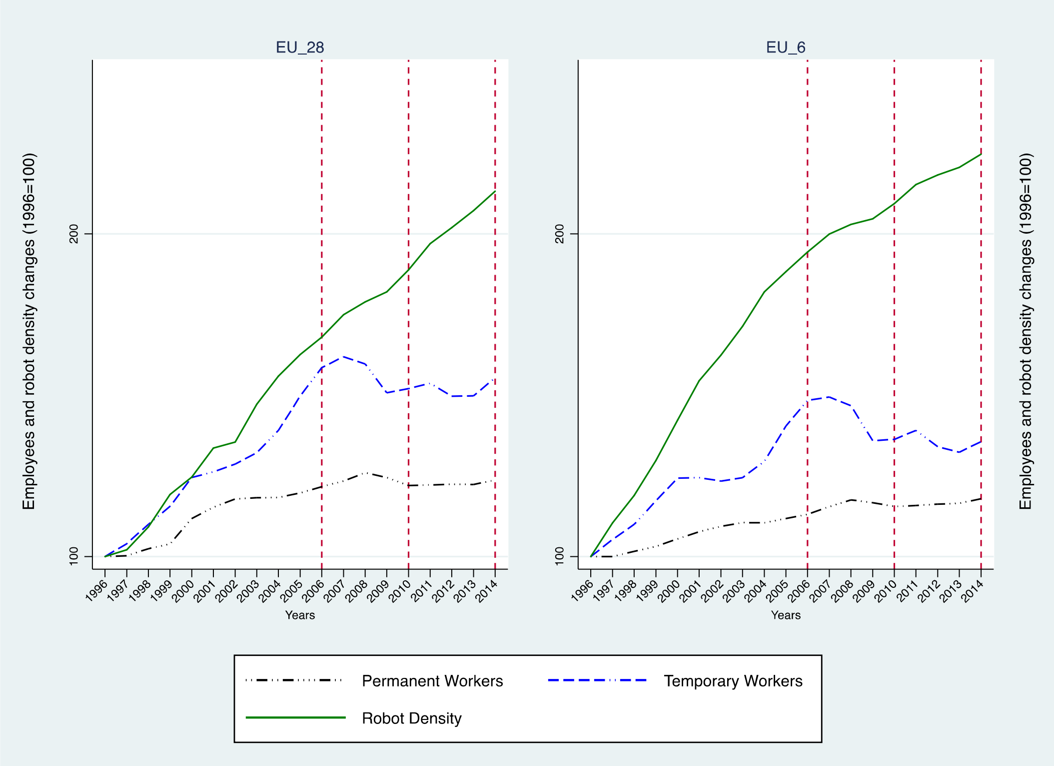
Tab 3 Probability to get a temporary job and robot exposure by seniority, skills and education of workers (**IV Probit, Control Function approach**, average partial effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Rob_exp x Work_30-64			**Rob_exp x Skills**			**Rob_exp x Education**		
	Total	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum
Endogenous Variables										
Rob_exposure	-0.003***	0.000	-0.000	0.000	-0.001	0.000	0.000	0.001***	0.000	0.001**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Rob x Work_30-64		0.000	-0.001	0.000						
		(0.001)	(0.000)	(0.001)						
Rob x Med_skilled					0.000	0.002***	0.000			
					(0.000)	(0.001)	(0.000)			
Rob x High_skilled					-0.001***	0.002***	-0.001***			
					(0.000)	(0.001)	(0.000)			
Rob x Sec_Educ								-0.001***	0.001***	-0.0005***
								(0.000)	(0.000)	(0.000)
Rob x Tert_Educ								-0.002***	0.001**	-0.002***
								(0.000)	(0.001)	(0.000)
Control Function: Residuals										
Rob_exposure_Res	0.002**	-0.000	-0.003**	0.000	-0.000	0.001	-0.000	-0.001**	0.002	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)
Rob x Work_30-64_Res		0.000	0.005***	0.000						
		(0.000)	(0.000)	(0.000)						
Rob x Med_skilled_Res					0.000	-0.002**	0.000			
					(0.000)	(0.001)	(0.000)			
Rob x High_skilled_Res					0.001***	-0.002*	0.001***			
					(0.000)	(0.001)	(0.000)			
Rob x Sec_Educ_Res								0.001***	-0.003***	0.0004***
								(0.000)	(0.001)	(0.0002)
Robx Tert_Educ_Res								0.002***	-0.002***	0.002***
								(0.000)	(0.001)	(0.000)
Other controls (as inTable 2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,137,288	1,137,288	367,936	769,352	1,137,288	367,936	769,352	1,137,288	367,936	769,352

*Note: Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robot-exposure is a country-industry level variable calculated as cumulative change of number of industrial robots over periods 1996-2006; 2000-2010 and 2004-2014 on country-industry level employees in 1995. All other variables refer to years 2006, 2010, 2014. Control function residuals are from the first stage regressions; their statistical significance signals endogeneity of robot exposure and its interaction terms (Wooldridge, 2015). Main effects for age, skills, education and all other control variables reported in Table 2 have been used in the estimations and omitted from this Table to improve the readability (they are available upon request). Total corresponds to the whole sample (12 industries), that is in turn composed by Hi-Cum* and *Low-Cum industries according to the Peneder's taxonomy discussed in section 3 and reported in Table1.*

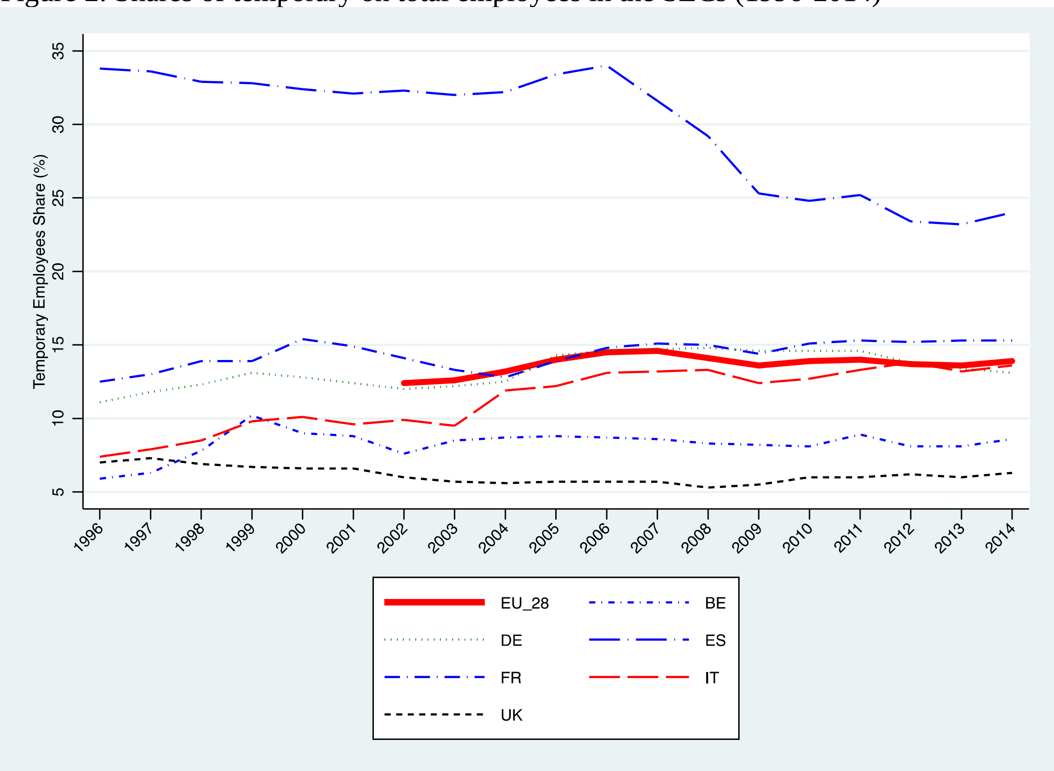
FIGURES

Figure 1: Robot density and employment growth in the SECs and EU-28 (1996-2014)



Source: OECD Statistics, Labour Force Survey; International Federation of Robotics (IFR).
Note: EU-6 includes Belgium, France, Germany, Spain, Italy, United Kingdom.
Robots and employment refer to all industries. Numbers of robots are normalised by OECD employment statistics

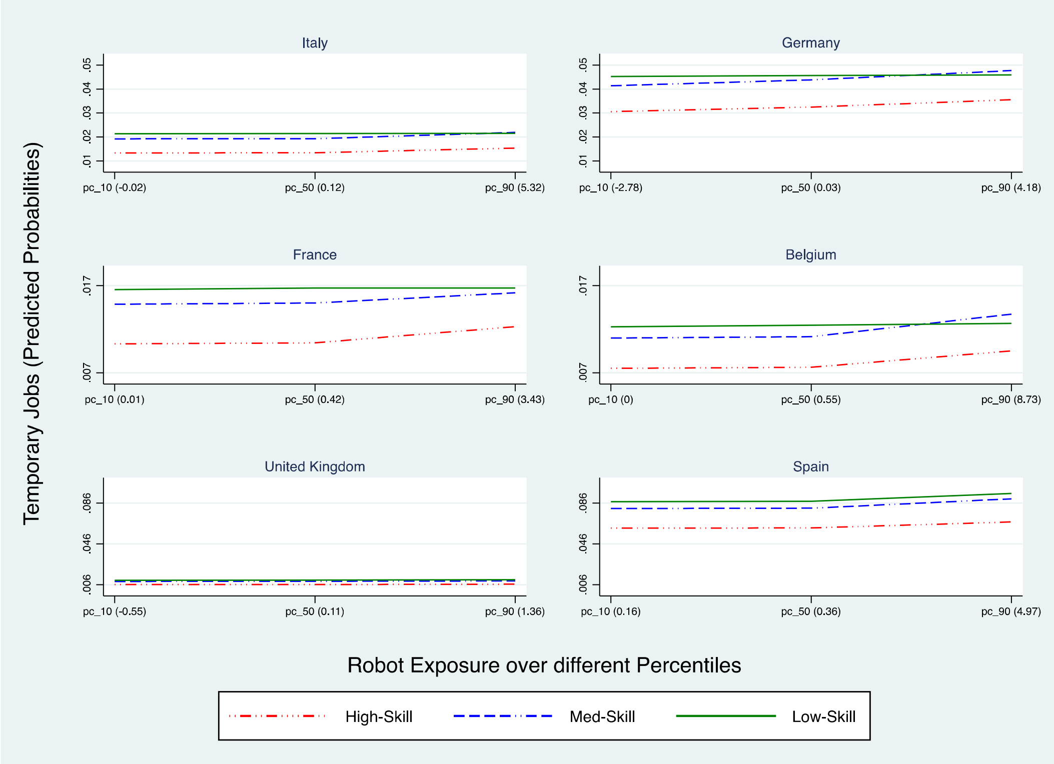
Figure 2: Shares of temporary on total employees in the SECs (1996-2014)



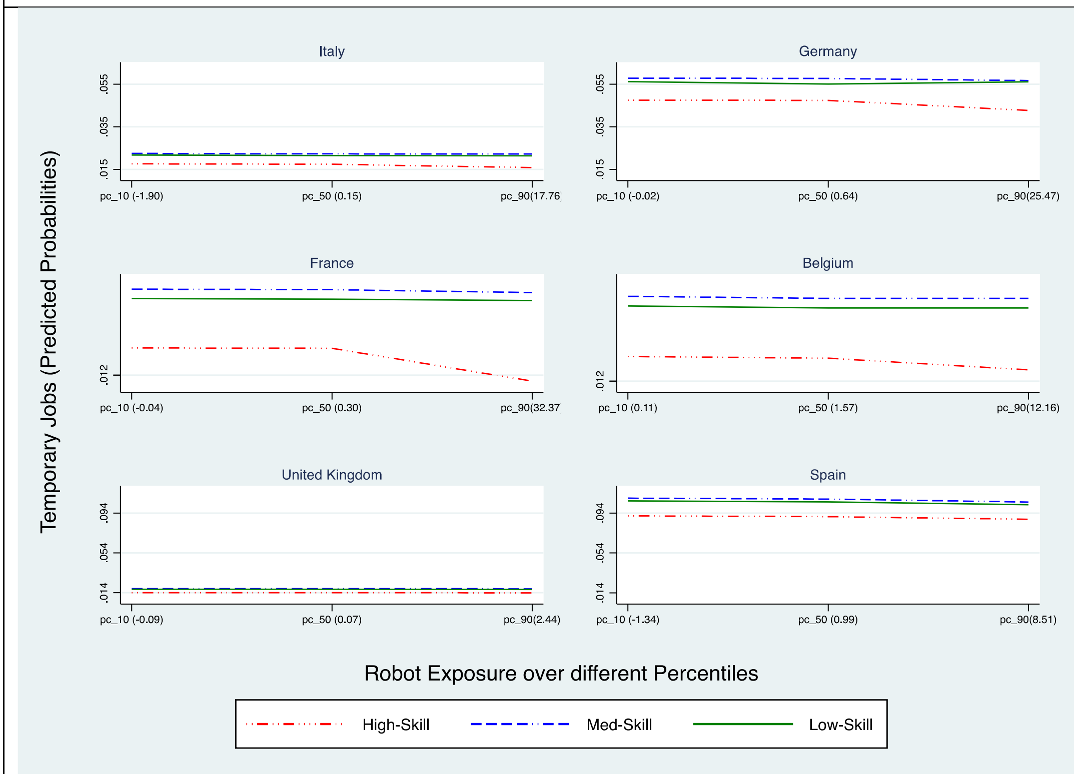
Source: *OECD Statistics, Labour Force Survey*

Figure 3 Temporary jobs, robot exposure and skills across countries

A. Low-Cum Industries: predicted probabilities for temporary jobs over robot exposure



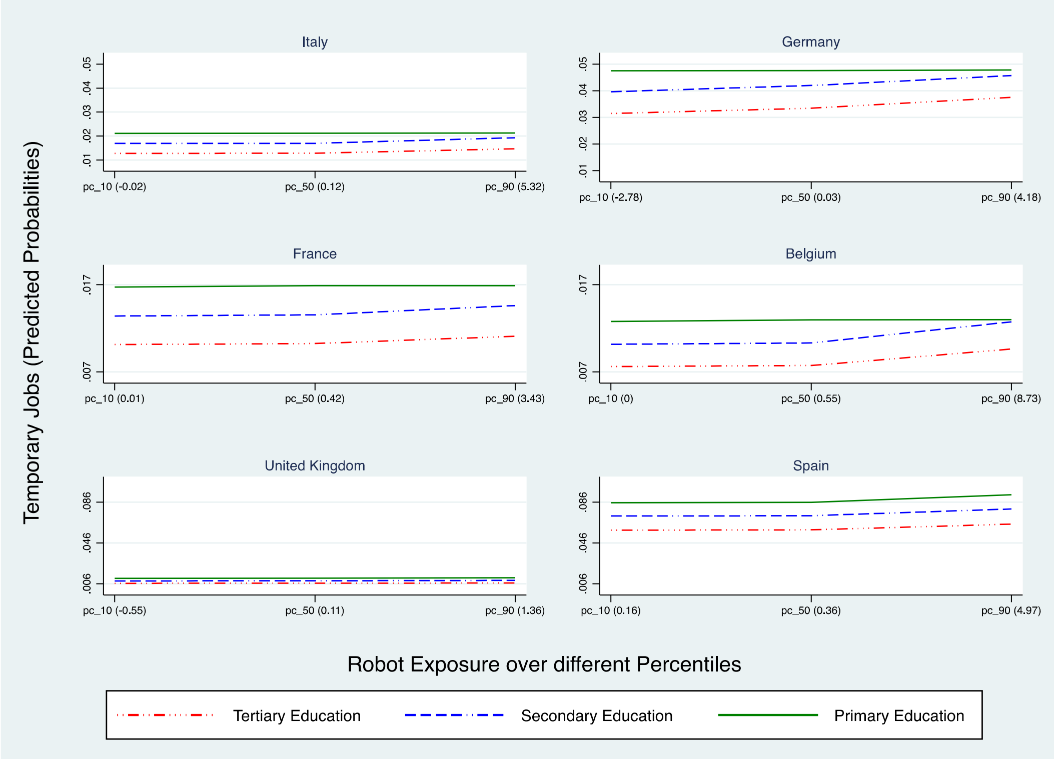
B. Hi-Cum Industries: predicted probabilities for temporary jobs over robot exposure



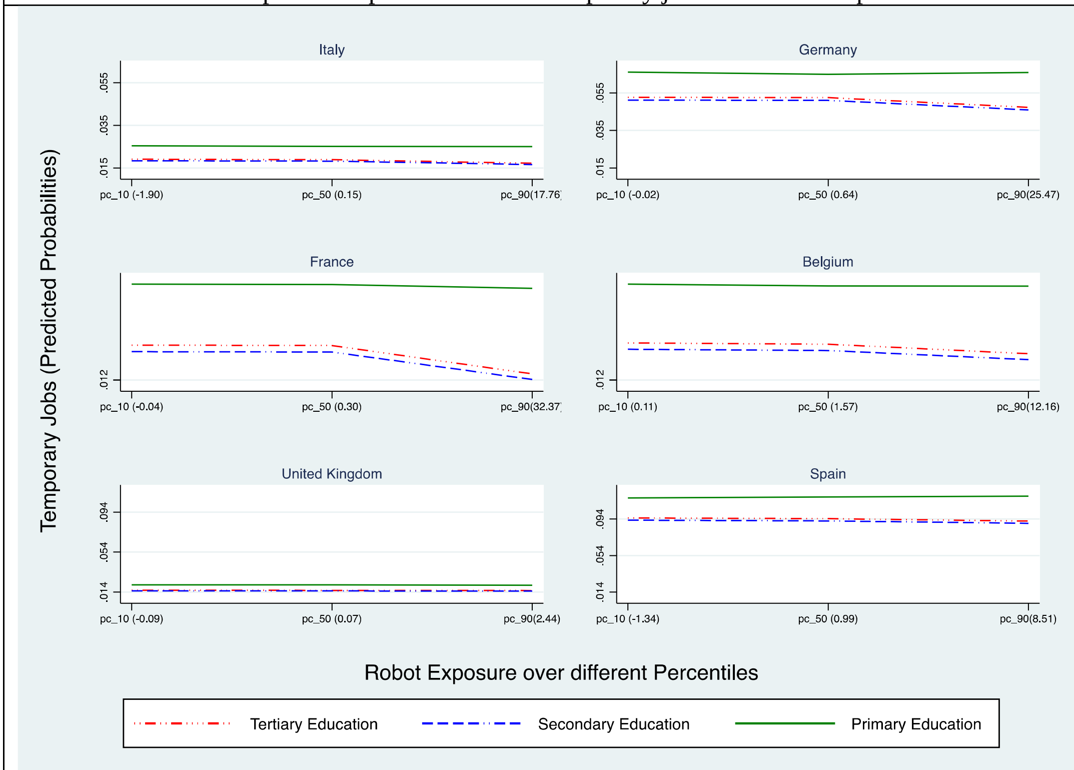
Note: Predicted probabilities have been estimated from econometric models reported in Table 3 (columns 6 and 7), given that i) Robot-exposure is set to country-specific percentiles reported in parentheses in this figure (pc_10; pc_50 and pc_90 stand for 10^th^, median and 90^th^ percentiles, respectively) ;ii) country is specified one at a time; iii) Skill categories are set at 1, one at a time; iii) the rest of predictors are set to their mean values.

Figure 4 Temporary jobs, robot exposure and education across countries

A. Low-Cum Industries: predicted probabilities for temporary jobs over robot exposure



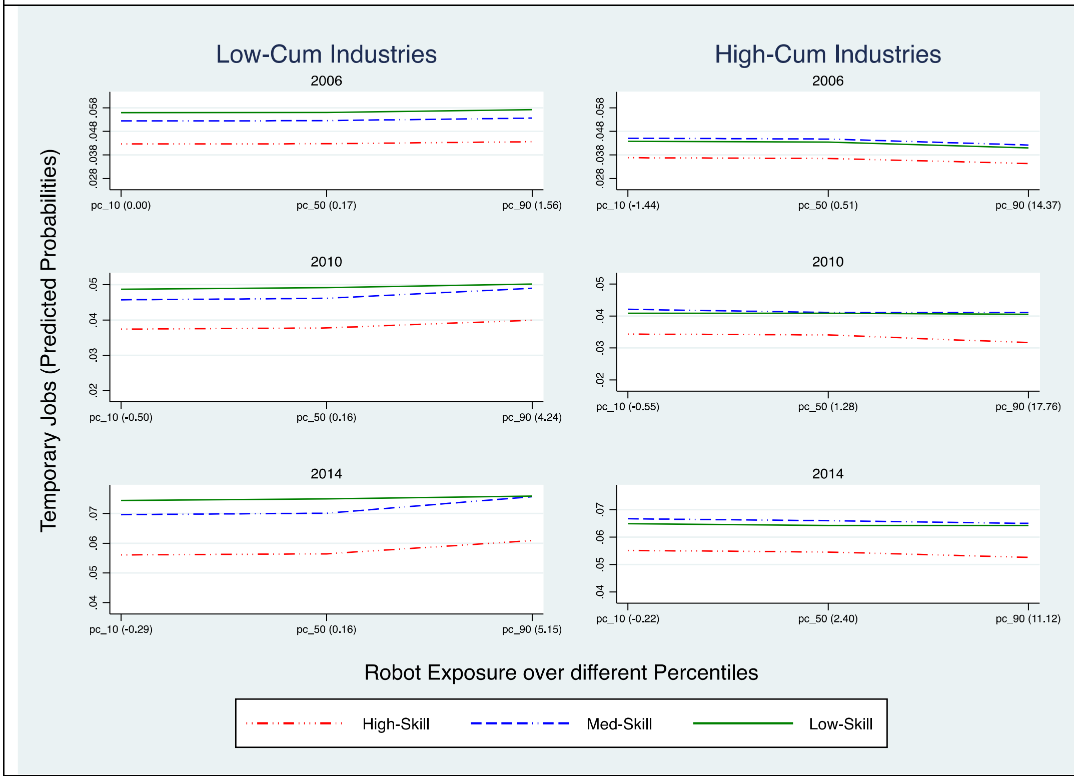
B. Hi-Cum Industries: predicted probabilities for temporary jobs over robot exposure



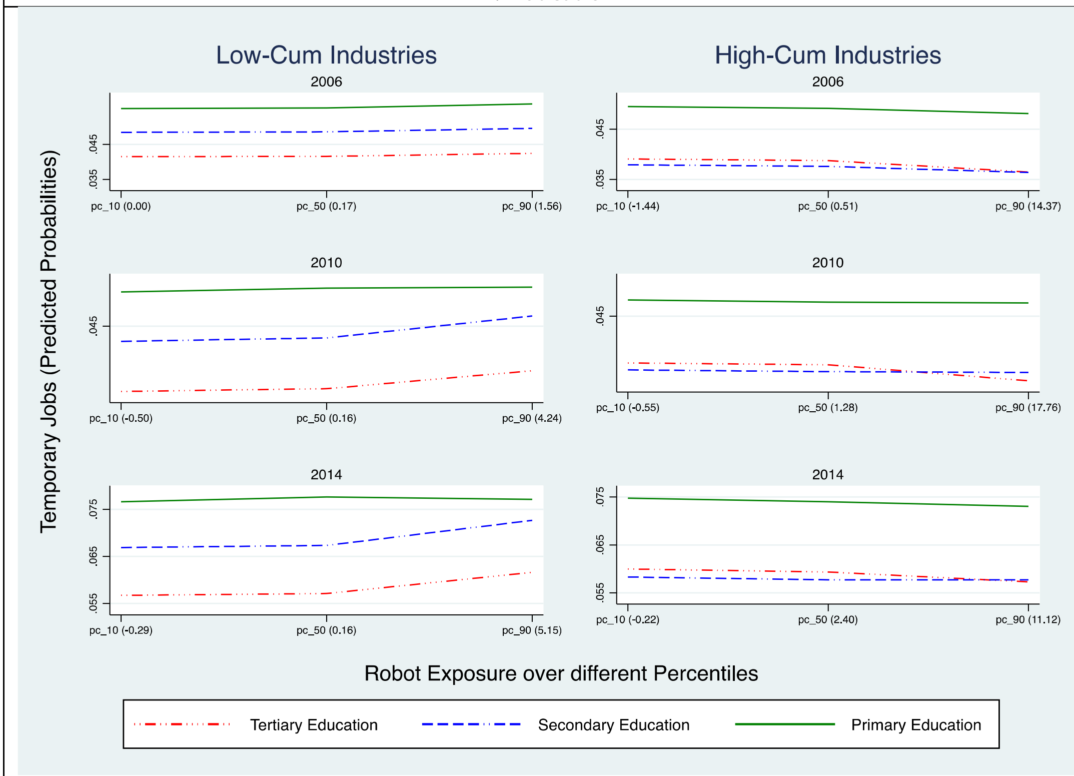
Note: Predicted probabilities have been estimated from econometric models reported in Table 3 (columns 9 and 10), given that i) Robot-exposure is set to country-specific percentiles reported in parentheses in this figure (pc_10; pc_50 and pc_90 stand for 10th, median and 90th percentiles, respectively);ii) country is specified one at a time; iii) Education categories are set at 1, one at a time; iii) the rest of predictors are set to their mean values.

Figure 5 Temporary jobs, robot exposure skills and education over years

A. Skills



B. Education



Note: Predicted probabilities have been estimated from econometric models reported in Table 3 (columns 6, 7, 9 and 10) given that i) Robot-exposure is set to high-cum and low-cum industries specific percentiles (averaged over six countries) reported in parentheses in this figure (pc_10; pc_50 and pc_90 stand for 10th, median and 90th percentiles, respectively); ii) year is specified one at a time; iii) Skills and Education categories are set at 1, one at a time; iii) the rest of predictors are set to their mean values.

APPENDIX

Table A.1 Temporary workers, tenure, wages and hours worked across characteristics

	Temp. workers/total employees (%)		**Hourly wages_ratio of temp./perm. workers (%)**	
Characteristics/Industries	*Low-Cum*	*High-Cum*	*Low-Cum*	*High-Cum*
Age_15_29	13.45	10.11	95.42	91.09
Age_30_64	3.19	2.88	75.84	82.70
Low-Skill	7.32	6.15	82.30	84.16
Mid-Skill	4.24	3.86	87.00	83.92
High_Skill	4.35	2.39	76.82	77.28
Primary Education	7.61	4.52	87.34	87.86
Secondary Education	3.85	3.66	76.38	75.42
Tertiary Education	5.68	3.15	72.61	77.59
	Tenure		**Hours worked annually_ratio of temp./perm. workers (%)**	
Characteristics/Industries	*Low-Cum*	*High-Cum*	*Low-Cum*	*High-Cum*
Age_15_29	3.52	3.61	94.71	88.35
Age_30_64	13.06	13.66	89.34	87.40
Low-Skill	9.60	10.11	87.34	87.86
Mid-Skill	12.25	12.52	76.38	75.42
High_Skill	11.62	13.78	72.61	77.59
Primary Education	12.81	12.50	87.67	84.52
Secondary Education	12.29	12.78	93.96	88.46
Tertiary Education	9.67	10.92	91.48	88.11

Source: SES_2006, 2010 and 2014. Note: own calculations from SES sample already reported in Table 1. All values are percentages with the exception of tenure that is reported in number of years.

Table A.2 Probability to get a temporary job and robot exposure by seniority, skills and education of workers. Control for trade exposure to World (**IV Probit, Control Function approach**, average partial effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Rob_exp x Work_30-64			**Rob_exp x Skills**			**Rob_exp x Education**		
	Total	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum
Endogenous Variables										
Rob_exposure	-0.003***	0.000	-0.000	-0.000	0.001**	0.000	0.000	0.001***	-0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Rob x Work_30-64		0.000	-0.000	-0.000						
		(0.000)	(0.000)	(0.000)						
Rob x Med_skilled					0.000	0.001***	0.000			
					(0.000)	(0.000)	(0.000)			
Rob x High_skilled					-0.001***	0.001*	-0.001***			
					(0.000)	(0.000)	(0.000)			
Rob x Sec_Educ								-0.001***	0.001**	-0.0003***
								(0.000)	(0.000)	(0.000)
Rob x Tert_Educ								-0.002***	0.001*	-0.002***
								(0.000)	(0.000)	(0.000)
Trade_exposure (World)	***-0.0002****	***0.000***	***0.000***	***-0.0002*****	***-0.0004****	***0.000***	***0.000***	***-0.000***	***0.000***	***-0.0001*****
	(0.000)	***(0.000)***	***(0.000)***	***(0.001)***	***(0.0002)***	***(0.000)***	***(0.000)***	***(0.000)***	***(0.000)***	***(0.000)***
Control Function: Residuals										
Rob_exposure_Res	-0.0002***	-0.000	-0.001	0.000	0.000	-0.000	-0.000	-0.001**	0.003*	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
Rob x Work_30-64_Res		-0.000	0.005***	0.000						
		(0.000)	(0.000)	(0.000)						
Rob x Med_skilled_Res					0.000	-0.001***	0.000			
					(0.000)	(0.000)	(0.000)			
Rob x High_skilled_Res					0.001***	-0.001*	0.001***			
					(0.000)	(0.000)	(0.000)			
Rob x Sec_Educ_Res								0.001***	-0.002***	0.0003***
								(0.000)	(0.000)	(0.0002)
Robx Tert_Educ_Res								0.001***	-0.002*	0.001***
								(0.000)	(0.001)	(0.000)
Other controls (as inTable 2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	879,617	879,617	241,158	637,342	879,617	241,158	637,342	879,617	241,158	637,342

*Note: Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robot-exposure is a country-industry level variable calculated as cumulative change of number of industrial robots over periods 1996-2006; 2000-2010 and 2004-2014 on country-industry level employees in 1995. Trade-exposure (World), is a country-industry level variable calculated as cumulative change of net exports to the world partner countries on wage bill (see Dauth et al., 2021) over periods 1996-2006; 2000-2010 and 2004-2014. All other variables refer to years 2006, 2010, 2014. Control function residuals are from the first stage regressions; their statistical significance signals endogeneity of robot exposure and its interaction terms (Wooldridge, 2015). Main effects for age, skills, education and all other control variables reported in Table 2 have been used in the estimations and omitted from this Table to improve the readability (they are available upon request). Total corresponds to the whole sample (12 industries), that is in turn composed by Hi-Cum* and *Low-Cum industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1. The lower number of observations compared to those of Table 3 is due to some missing values for country-industry level variable Trade_exposure (World).*

Table A.3 Probability to get a temporary job and robot exposure by seniority, skills and education of workers. Control for trade exposure to Japan and South Korea (**IV Probit, Control Function approach**, average partial effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Rob_exp x Work_30-64			**Rob_exp x Skills**			**Rob_exp x Education**		
	Total	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum
Endogenous Variables										
Rob_exposure	0.000	0.000	0.000	-0.000	0.001**	0.000	0.000	0.001***	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Rob x Work_30-64		0.000	0.000	-0.000						
		(0.000)	(0.000)	(0.001)						
Rob x Med_skilled					0.000	0.001***	0.000			
					(0.000)	(0.000)	(0.000)			
Rob x High_skilled					-0.001***	0.001*	-0.001***			
					(0.000)	(0.000)	(0.000)			
Rob x Sec_Educ								-0.001***	0.000	-0.0005***
								(0.000)	(0.000)	(0.000)
Rob x Tert_Educ								-0.002***	0.001*	-0.002***
								(0.000)	(0.000)	(0.000)
Trade_exposure (Japan_Korea)	***-0.000***	***0.000***	***0.000***	***-0.000***	***-0.0004****	***0.000***	***0.000***	***-0.0007****	***0.000***	***-0.000***
	(0.000)	***(0.000)***	***(0.000)***	***(0.000)***	***(0.0002)***	***(0.000)***	***(0.000)***	***(0.0002)***	***(0.000)***	***(0.000)***
Control Function: Residuals										
Rob_exposure_Res	-0.000	-0.000	-0.002**	0.000	0.000	-0.000	-0.000	-0.001**	0.003**	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Rob x Work_30-64_Res		0.000	0.005***	0.000						
		(0.000)	(0.001)	(0.000)						
Rob x Med_skilled_Res					0.000	-0.001***	0.000			
					(0.000)	(0.000)	(0.000)			
Rob x High_skilled_Res					0.001***	-0.001*	0.001***			
					(0.000)	(0.000)	(0.000)			
Rob x Sec_Educ_Res								0.001***	-0.002***	0.0004***
								(0.000)	(0.000)	(0.0002)
Robx Tert_Educ_Res								0.002***	-0.002**	0.002***
								(0.000)	(0.001)	(0.000)
Other controls (as inTable 2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	997,810	997,810	241,308	756,308	997,810	241,308	756,308	997,810	241,308	756,308

*Note: Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robot-exposure is a country-industry level variable calculated as cumulative change of number of industrial robots over periods 1996-2006; 2000-2010 and 2004-2014 on country-industry level employees in 1995. Trade-exposure (Japan-Korea), is a country-industry level variable calculated as cumulative change of net exports to Japan and South Korea on wage bill (see Dauth et al., 2021) over periods 1996-2006; 2000-2010 and 2004-2014. All other variables refer to years 2006, 2010, 2014.Control function residuals are from the first stage regressions; their statistical significance signals endogeneity of robot exposure and its interaction terms (Wooldridge, 2015). Main effects for age, skills, education and all other control variables reported in Table 2 have been used in the estimations and omitted from this Table to improve the readability (they are available upon request). Total corresponds to the whole sample (12 industries), that is in turn composed by Hi-Cum* and *Low-Cum industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1. The lower number of observations compared to those of Table 3 is due to some missing values for country-industry level variable Trade_exposure (Japan_Korea).*

Tab A.4 Probability to get a temporary job and robot exposure by seniority, skills and education of workers. Five countries excluding Spain (**IV Probit, Control Function approach**, average partial effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Rob_exp x Work_30-64			**Rob_exp x Skills**			**Rob_exp x Education**		
	Total	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum	Total	Low_Cum	Hi-Cum
Endogenous Variables										
Rob_exposure	-0.003***	-0.001	-0.002	-0.001*	-0.000	-0.002	0.000	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)
Rob x Work_30-64		-0.0002*	0.001***	-0.0002**						
		(0.0001)	(0.000)	(0.000)						
Rob x Med_skilled					-0.000	0.002***	-0.000			
					(0.000)	(0.001)	(0.000)			
Rob x High_skilled					-0.001***	0.002***	-0.001***			
					(0.000)	(0.001)	(0.000)			
Rob x Sec_Educ								-0.0004***	0.001***	-0.0004***
								(0.000)	(0.000)	(0.000)
Rob x Tert_Educ								-0.002***	0.001**	-0.002***
								(0.000)	(0.001)	(0.000)
Control Function: Residuals										
Rob_exposure _Res	0.002**	0.001	0.001	0.001*	-0.000	0.002	-0.000	0.000	0.002	-0.000
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)
Rob x Work_30-64_Res		0.000	0.001***	0.000						
		(0.000)	(0.000)	(0.000)						
Rob x Med_skilled_ Res					0.0005***	-0.001*	0.0004*			
					(0.000)	(0.000)	(0.000)			
Rob x High_skilled_ Res					0.001***	-0.002*	0.001***			
					(0.000)	(0.001)	(0.000)			
Rob x Sec_Educ_Res								0.0005***	-0.001**	0.0005***
								(0.000)	(0.000)	(0.0002)
Robx Tert_Educ_Re s								0.002***	-0.002**	0.002***
								(0.000)	(0.001)	(0.000)
Other controls (as inTable 2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	972,891	972,891	305,134	667,127	972,891	305,134	667,127	972,891	305,134	667,127

*Note: Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Observations for Spain have been omitted from the sample. Robot-exposure is a country-industry level variable calculated as cumulative change of number of industrial robots over periods 1996-2006; 2000-2010 and 2004-2014 on country-industry level employees in 1995. All other variables refer to years 2006, 2010, 2014. Control function residuals are from the first stage regressions; their statistical significance signals endogeneity of robot exposure and its interaction terms (Wooldridge, 2015). Main effects for age, skills, education and all other control variables reported in Table 2 have been used in the estimations and omitted from this Table to improve the readability (they are available upon request). Total corresponds to the whole sample (12 industries), that is in turn composed by Hi-Cum* and *Low-Cum industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1.*

Table A.5 First Stage (OLS estimations) from IV_CF Probit Model reported in Table 3.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total	**Rob_exp x Work_30-64**			**Rob_exp x Skills**			**Rob_exp x Education**		
	Total	Total	Low_Cum	Hi_Cum	Total	Low_Cum	Hi_Cum	Total	Low_Cum	Hi_Cum
Dependent variables	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp
Excluded Instruments										
Rob_exp_Jp_Kr	0.403***	0.291***	1.601***	0.304***	0.458***	2.452***	0.470***	0.345 ***	1.769***	0.349 ***
	(0.000)	(0.009)	(0.038)	(0.009)	(0.012)	(0.042)	(0.112)	(0.011)	(0.039)	(0.011)
Dependent variables		RobxWork	RobxWork	RobxWork						
Excluded Instruments										
RobxWork_Jp_Kr		0.405***	3.074***	0.400***						
		(0.013)	(0.028)	(0.013)						
Dependent variables					RobxMskill	RobxMskill	RobxMskill			
Excluded Instruments										
RobxMskill _Jp_Kr					0.785***	2.344***	0.783***			
					(0.011)	(0.045)	(0.011)			
Dependent variables					Robx_Hskill	Robx_Hskill	Robx_Hskill			
Excluded Instruments										
Robx_Hskill_Jp_Kr					0.784***	3.412***	0.780***			
					(0.017)	(0.051)	(0.017)			
Dependent variables								RobxSecEduc	RobxSecEduc	RobxSecEduc
Excluded Instruments										
RobxSecEduc _Jp_Kr								0.477***	3.361***	0.461***
								(0.011)	(0.027)	(0.011)
Dependent variables								RobxTerEduc	RobxTerEduc	RobxTerEduc
Excluded Instruments										
RobxTerEduc _Jp_Kr								0.265***	2.861***	0.261***
								(0.015)	(0.034)	(0.014)
Included Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,137,288	1,137,288	367,936	769,352	1,137,288	367,936	769,352	1,137,288	367,936	769,352
Kleibergen-Paap Wald rk F statistic	1381.76	705.48	1159.51	767.71	446.43	685.27	472.50	455.24	805.33	492.85

*Note: Establishment level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables are i) the endogenous variable Robot Exposure (Rob_exp), ii) the interaction Rob x Workers_30-64 (RobxWork); iii) the interactions Robots x Med_skilled (RobxMskill) and Robots x High_skilled (Robx_Hskill); iv) the interactions Robots x Secondary_education (RobxSecEduc) and Robots x Tertiary_Education (Robx_TerEduc). The set of excluded instruments includes average robot exposure of Japan and South Korea at the industry level and its interaction terms. The included instruments are all the exogenous variables reported in Table 3. Kleibergen-Paap Wald rk F statistic is a test for detecting weak instruments, that is, instruments poorly correlated with the endogenous variable. A rule of thumb is considering instruments as relevant (no weak) when the F statistics is above 10 (Baum et al., 2007). Total is the whole sample, High & Medium Cumulativeness (Hi-Cum) and Low-Cumulativeness (Low-Cum) group industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1.*

Table A.6 First Stage (OLS estimations) from IV_CF Probit Model reported in Table A.2 (Control for trade exposure to World).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total	**Rob_exp x Work_30-64**			**Rob_exp x Skills**			**Rob_exp x Education**		
	Total	Total	Low_Cum	Hi_Cum	Total	Low_Cum	Hi_Cum	Total	Low_Cum	Hi_Cum
Dependent variables	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp
Excluded Instruments										
Rob_exp_Jp_Kr	0.400***	0.293***	2.161***	0.292***	0.461***	2.979***	0.463***	0.347 ***	2.092***	0.337 ***
	(0.010)	(0.009)	(0.057)	(0.008)	(0.012)	(0.057)	(0.011)	(0.010)	(0.056)	(0.010)
Dependent variables		RobxWork	RobxWork	RobxWork						
Excluded Instruments										
RobxWork_Jp_Kr		0.394***	3.064***	0.388***						
		(0.013)	(0.032)	(0.013)						
Dependent variables					RobxMskill	RobxMskill	RobxMskill			
Excluded Instruments										
RobxMskill _Jp_Kr					0.776***	2.337***	0.778***			
					(0.011)	(0.052)	(0.010)			
Dependent variables					Robx_Hskill	Robx_Hskill	Robx_Hskill			
Excluded Instruments										
Robx_Hskill_Jp_Kr					0.773***	3.550***	0.771***			
					(0.017)	(0.062)	(0.017)			
Dependent variables								RobxSecEduc	RobxSecEduc	RobxSecEduc
Excluded Instruments										
RobxSecEduc _Jp_Kr								0.468***	3.626***	0.453***
								(0.011)	(0.032)	(0.010)
Dependent variables								RobxTerEduc	RobxTerEduc	RobxTerEduc
Excluded Instruments										
RobxTerEduc _Jp_Kr								0.252***	2.940***	0.251***
								(0.014)	(0.039)	(0.014)
Trade_exposure (World)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Included Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	879,617	879,617	241,158	637,342	879,617	241,158	637,342	879,617	241,158	637,342
Kleibergen-Paap Wald rk F statistic	1535.39	741.25	851.47	747.84	467.60	541.49	479.15	478.79	605.15	526.94

*Note: Establishment level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables are i) the endogenous variable Robot Exposure (Rob_exp), ii) the interaction Rob x Workers_30-64 (RobxWork); iii) the interactions Robots x Med_skilled (RobxMskill) and Robots x High_skilled (Robx_Hskill); iv)); iii) the interactions Robots x Secondary_education (RobxSecEduc) and Robots x Tertiary_Education (Robx_TerEduc). The set of excluded instruments includes average robot exposure of Japan and South Korea at the industry level and its interaction terms. Trade Exposure and Other included instruments are the exogenous variables reported in Table A.2. Kleibergen-Paap Wald rk F statistic is a test for detecting weak instruments, that is, instruments poorly correlated with the endogenous variable. A rule of thumb is considering instruments as relevant (no weak) when the F statistics is above 10 (Baum et al., 2007). Total is the whole sample, High & Medium Cumulativeness (Hi-Cum) and Low-Cumulativeness (Low-Cum) group industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1.*

Table A.7 First Stage (OLS estimations) from IV_CF Probit Model reported in Table A.3 (Control for trade exposure to Japan and South Korea).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total	**Rob_exp x Work_30-64**			**Rob_exp x Skills**			**Rob_exp x Education**		
Sample	Total	Total	Low_Cum	Hi_Cum	Total	Low_Cum	Hi_Cum	Total	Low_Cum	Hi_Cum
Dependent variables	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp
Excluded Instruments										
Rob_exp_Jp_Kr	0.325***	0.292***	2.834***	0.302***	0.459***	3.716 ***	0.467***	0.346 ***	2.762 ***	0.347 ***
	(0.009)	(0.009)	(0.058)	(0.009)	(0.012)	(0.054)	(0.012)	(0.011)	(0.055)	(0.011)
Dependent variables		RobxWork	RobxWork	RobxWork						
Excluded Instruments										
RobxWork_Jp_Kr		0.401***	3.039***	0.399***						
		(0.013)	(0.033)	(0.013)						
Dependent variables					RobxMskill	RobxMskill	RobxMskill			
Excluded Instruments										
RobxMskill _Jp_Kr					0.781***	2.296 ***	0.784***			
					(0.011)	(0.053)	(0.011)			
Dependent variables					Robx_Hskill	Robx_Hskill	Robx_Hskill			
Excluded Instruments										
Robx_Hskill_Jp_Kr					0.779***	3.531***	0.778***			
					(0.017)	(0.062)	(0.017)			
Dependent variables								RobxSecEduc	RobxSecEduc	RobxSecEduc
Excluded Instruments										
RobxSecEduc _Jp_Kr								0.472***	3.650 ***	0.460***
								(0.011)	(0.032)	(0.011)
Dependent variables								RobxTerEduc	RobxTerEduc	RobxTerEduc
Excluded Instruments										
RobxTerEduc _Jp_Kr								0.260***	2.939***	0.259***
								(0.014)	(0.039)	(0.014)
Trade_exposure (Japan_Korea)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Included Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	997,810	997,810	241,308	756,308	997,810	241,308	756,308	997,810	241,308	756,308
Kleibergen-Paap Wald rk F statistic	1434.88	719.66	1379.45	760.39	451.942	813.34	468.50	461.47	972.08	488.64

*Note: Establishment level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables are i) the endogenous variable Robot Exposure (Rob_exp), ii) the interaction Rob x Workers_30-64 (RobxWork); iii) the interactions Robots x Med_skilled (RobxMskill) and Robots x High_skilled (Robx_Hskill); iv)); iii) the interactions Robots x Secondary_education (RobxSecEduc) and Robots x Tertiary_Education (Robx_TerEduc). The set of excluded instruments includes average robot exposure of Japan and South Korea at the industry level and its interaction terms. Trade Exposure and Other included instruments are the exogenous variables reported in Table A.3. Kleibergen-Paap Wald rk F statistic is a test for detecting weak instruments, that is, instruments poorly correlated with the endogenous variable. A rule of thumb is considering instruments as relevant (no weak) when the F statistics is above 10 (Baum et al., 2007). Total is the whole sample, High & Medium Cumulativeness (Hi-Cum) and Low-Cumulativeness (Low-Cum) group industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1.*

Table A.8 First Stage (OLS estimations) from IV_CF Probit Model reported in Table A.4 (Five countries excluding Spain).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total	**Rob_exp x Work_30-64**			**Rob_exp x Skills**			**Rob_exp x Education**		
Sample	Total	Total	Low_Cum	Hi_Cum	Total	Low_Cum	Hi_Cum	Total	Low_Cum	Hi_Cum
Dependent variables	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp	Rob_exp
Excluded Instruments										
Rob_exp_Jp_Kr	0.422***	0.211***	1.627***	0.224***	0.341***	2.264***	0.354***	0.242 ***	1.952***	0.250 ***
	(0.012)	(0.010)	(0.046)	(0.010)	(0.013)	(0.050)	(0.013)	(0.012)	(0.053)	(0.012)
Dependent variables		RobxWork	RobxWork	RobxWork						
Excluded Instruments										
RobxWork_Jp_Kr		0.424***	3.183***	0.422***						
		(0.014)	(0.032)	(0.014)						
Dependent variables					RobxMskill	RobxMskill	RobxMskill			
Excluded Instruments										
RobxMskill _Jp_Kr					0.759***	2.956***	0.750***			
					(0.013)	(0.056)	(0.013)			
Dependent variables					Robx_Hskill	Robx_Hskill	Robx_Hskill			
Excluded Instruments										
Robx_Hskill_Jp_Kr					0.787***	3.515***	0.784***			
					(0.019)	(0.062)	(0.019)			
Dependent variables								RobxSecEduc	RobxSecEduc	RobxSecEduc
Excluded Instruments										
RobxSecEduc _Jp_Kr								0.498***	3.400***	0.487***
								(0.012)	(0.032)	(0.012)
Dependent variables								RobxTerEduc	RobxTerEduc	RobxTerEduc
Excluded Instruments										
RobxTerEduc _Jp_Kr								0.299***	2.830***	0.299***
								(0.016)	(0.043)	(0.016)
Included Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	972,891	972,891	305,134	667,127	972,891	305,134	667,127	972,891	305,134	667,127
Kleibergen-Paap Wald rk F statistic	1234.02	311.39	734.02	354.41	211.48	238.37	479.15	203.88	518.57	233.21

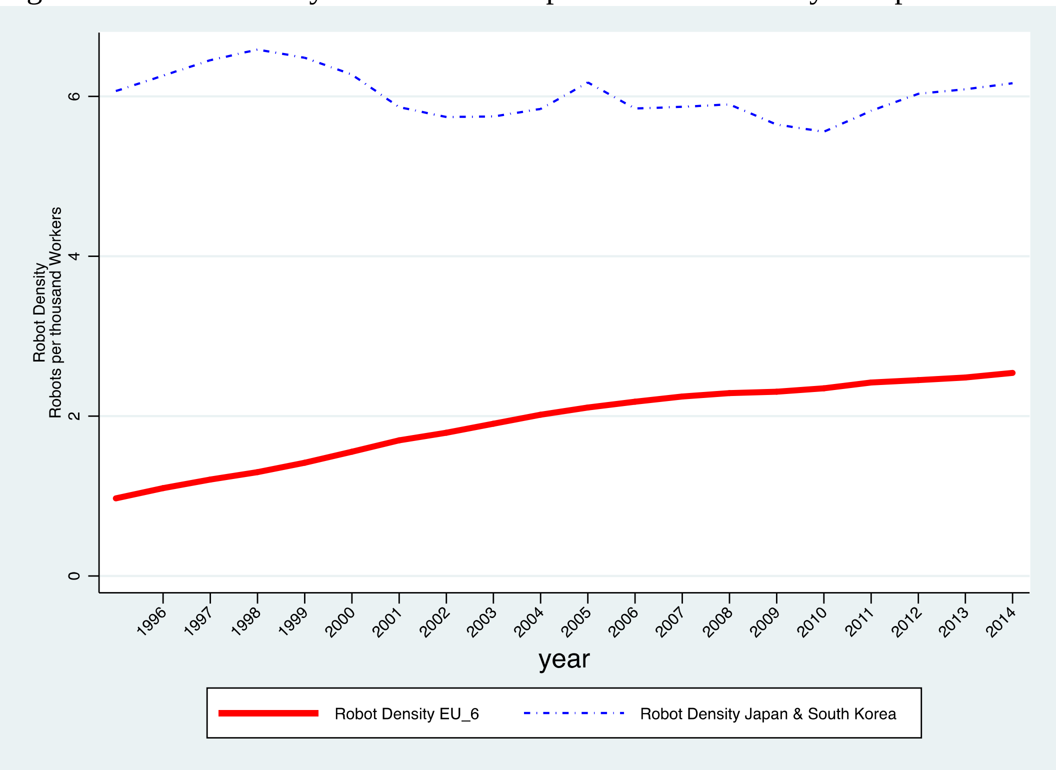
*Note: Establishment level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables are i) the endogenous variable Robot Exposure (Rob_exp), ii) the interaction Rob x Workers_30-64 (RobxWork); iii) the interactions Robots x Med_skilled (RobxMskill) and Robots x High_skilled (Robx_Hskill); iv) the interactions Robots x Secondary_education (RobxSecEduc) and Robots x Tertiary_Education (Robx_TerEduc). The set of excluded instruments includes average robot exposure of Japan and South Korea at the industry level and its interaction terms. The included instruments are all the exogenous variables reported in Table 3. Kleibergen-Paap Wald rk F statistic is a test for detecting weak instruments, that is, instruments poorly correlated with the endogenous variable. A rule of thumb is considering instruments as relevant (no weak) when the F statistics is above 10 (Baum et al., 2007). Total is the whole sample, High & Medium Cumulativeness (Hi-Cum) and Low-Cumulativeness (Low-Cum) group industries according to the Peneder's taxonomy discussed in section 3 and reported in Table 1.*

Table A.9 Group differences in Average Partial Effects estimated in Tables 3, A.2, A.3, A.4.

	APEs from Table 3			APEs from Table A.2		
	Low_Cum	Hi-Cum	**Diff: LowCum - HighCum**	Low_Cum	Hi-Cum	**Diff: LowCum - HighCum**
	(1)	(2)	(3)	(4)	(5)	(6)
Endogenous Variables						
Rob x Med_skilled	0.002***	0.000	**0.002*** **	0.001***	0.000	**0.001** **
	(0.001)	(0.000)	**(0.001)**	(0.000)	(0.000)	**(0.000)**
Rob x High_skilled	0.002***	-0.001***	**0.003*** **	0.000	-0.001***	**0.001*** **
	(0.001)	(0.000)	**(0.001)**	(0.000)	(0.000)	**(0.001)**
Rob x Sec_Educ	0.001***	-0.0005***	**0.002*** **	0.001**	-0.0003***	**0.0014*** **
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**
Rob x Tert_Educ	0.001**	-0.002***	**0.003*** **	0.001*	-0.002***	**0.003** **
	(0.001)	(0.000)	**(0.001)**	(0.000)	(0.000)	**(0.001)**
	APEs from Table A.3			APEs from Table A.4		
	Low_Cum	Hi-Cum	Diff: LowCum - HighCum	Low_Cum	Hi-Cum	**Diff: LowCum - HighCum**
	(7)	(8)	(9)	(10)	(11)	(12)
Endogenous Variables						
Rob x Med_skilled	0.001***	0.000	**0.001** **	0.002***	-0.000	**0.002*** **
	(0.000)	(0.000)	**(0.000)**	(0.001)	(0.000)	**(0.001)**
Rob x High_skilled	0.001*	-0.001***	**0.002** **	0.002***	-0.001***	**0.003*** **
	(0.000)	(0.000)	**(0.000)**	(0.001)	(0.000)	**(0.001)**
Rob x Sec_Educ	0.000	-0.0005***	**0.001** **	0.001***	-0.0004***	**0.0014*** **
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**
Rob x Tert_Educ	0.001*	-0.002***	**0.003*** **	0.001**	-0.002***	**0.003*** **
	(0.000)	(0.000)	**(0.001)**	(0.001)	(0.000)	**(0.001)**

*Note: Establishment level cluster-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1, 2, 4, 5, 7, 8, 10 and 11 show average partial effects (APEs) already reported in the tables above for the two sub-samples (groups) LowCum and HighCum. Columns 3, 6, 9 and 12 report the group differences between APEs and their standard errors. We follow Mize, Doan and Long (2019) by assuming non-zero cross-model covariance and applying a SUEST method where we re-estimated simultaneously APEs for Low- and High-Cum industries. The Stata's routine based on generalized structural equation modeling command gsem, that makes postestimation calculation of APEs much simpler, has been used.*

Figure A.1 Robot density in the EU-6 compared to robot density of Japan and Korea



OECD Statistics, Labour Force Survey; International Federation of Robotics (IFR). Note. Robots and employment refer to all industries. For these aggregated figures robots are normalised by OECD employment statistics.

[i] We also use additional data to normalise robots (EUKLEMS) or to perform robustness checks (Eurostat data for trade and national accounts, and UN Comtrade database for international trade in R&D).

[ii] Although SES is conducted over many European countries, singling out our sample was the result of a trade-off among a number of data limitations. First, many countries included in the SES dataset do not report a sufficient industry breakdown for correctly mapping economic activities into High & Medium and Low-Knowledge Cumulativeness industries. This is the case for Denmark and Finland. Germany also falls in this group in 2006. The importance of this country in terms of robot adoption led us to retain it for 2010 and 2014. Second, in many Eastern European countries, robot adoption figures are close to zero. Third, several countries are not covered in Peneder's study (2010) on knowledge cumulativeness. Unfortunately, for other countries such as Sweden, that is important in terms of robot adoption, SES does not report data for temporary workers. Fortunately, our sample includes the biggest five economies of the former EU-28 and, in 2014, they still account for 85% of all robots introduced in the EU-28.

[iii] Following Graetz & Michaels (2018), we do not use the IFR categories 'all other manufacturing', 'all other non-manufacturing', and 'unspecified'. This is because the bulk of robots from the latter three industries is included in 'Unspecified' and the risk of misallocation of these robots among industries is high. We use weights based on shares of employees to split robots in the R&D and in the Education sectors. The motivation is that Peneder's taxonomy does not include Education, but covers R&D as an industry with high knowledge cumulativeness (see Table 1).

[iv] Differently from Acemoglu & Restrepo (2020), our dependent variable is not the cumulated days of employment over years, but the probability to have a temporary job in 2006, 2010 and 2014 respectively. We assume that 10 years of robot exposure is a sufficient time to shape the propensity of firms to employ temporary workers.

[v] Eurostat, Statistics explained, online documents, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech

[vi] Since we have a hierarchical model with different potential levels for clustering, we follow the Abadie et al. (2022) suggestions to decide what to cluster over and assume that besides the assignment process, the sampling process and the level to which the heterogeneity of treatment emerges do matter. Despite robot exposure is at country-industry level, we have to consider that the Structure of Earnings Survey relies on a two-stages sample design, where a stratified sample of local units (establishments) is drawn in the first stage, and a simple sample of employees is taken within each of the selected local units, in the second stage. Further, almost all our key results stem from interactions between country-by-industry level *robot exposure* and individual level *age*, *skills* and *education*. It means that we should observe heterogeneity of the treatment (*robot exposure*) within the country-by-industry level cluster. Eventually, it is plausible to assume that, being other individual characteristics equal, the probability to get a temporary contract is correlated for employees within the same establishment/firm as result of a specific strategy conducted by companies. Even though we do not directly focus on the company level, we hypothesised different behaviour among companies in the same industry (see H.3b and H.3c) and control for their productivity dispersion (see discussion about its effects on section 5.1). For these reasons, we conjecture that correlation of errors at establishment level is more important than that at the country-by-industry level.

[vii] APE is the numerical derivative of the probability to get a temporary contract with respect to a variable of interest for each observation using the other covariates as they were observed, and then the average of all these individual marginal effects across the sample.

[viii] In high-cum industries (Table 3, column 10), robot exposure only reduces the probability to get temporary jobs for high-educated workers, whereas the APE is positive for individuals with both primary (0.001) and secondary educational attainments (-0.0005 + 0.001=+0.0005). We do not go through this result because it is not confirmed by robustness tests (see Tables A.2, A.3 and A.4, columns 10).

[ix] The total effect of robots for workers with secondary educational attainment (Rob x Sec_Educ) is the algebraic sum of the coefficients *Rob_Exposure + Rob x Sec_Educ*.

[x] Graetz and Michaels find that, unlike ICT, automation does not polarize the labor market, since the negative effects of robots on hours worked by the least educated workers are no lower than those of the middle skilled.

[xi] As already reported for results in Table 3, all the differences between the APEs of interest estimated across the two technological regimes (low- vs high-cum) in Tables A.2, A.3 and A.4, are statistically significant (see Table A.9, columns 6, 10 and 12).