Just reallocated? Robots, displacement and job quality

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Abstract

Concerns over widespread technological unemployment are often dismissed with the argument that human labour is not destroyed by automation but rather *reallocated* to other tasks, occupations or sectors. When focusing on pure employment levels, the idea that workers are not permanently excluded but "just" reallocated somewhere else might strike as reassuring. However, while quite some attention has been devoted to the impact of automation on employment levels, little has been said about the *quality* of the new match for displaced workers. Using an administrative longitudinal panel covering a large sample of Spanish workers for the period 2001-2017, we investigate the short- and medium-term re-employment prospects of workers displaced from sectors with an increasing density of industrial robots. Furthermore, we examine the role of reallocation to other sectors or local labour markets as an adjustment mechanism. Our analysis suggests that exposed middle- and low-skilled workers are more likely than non-exposed ones to be still unemployed six months after displacement. Among those who find a new occupation, an additional robot per 1000 workers increases the probability of being re-employed in a lower-paying job by about 2 percentage points for middle- and low-skilled workers, with the penalty being significantly higher for those who relocate to a different sector. Moreover, these workers tend to face a qualification downgrading in the new job and are more likely to be re-employed through temporary employment agencies. High-skilled workers are less negatively affected by exposure, although they sometimes also incur a penalty when changing sector.

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1 Introduction

Policy makers and economists have long worried about possible detrimental effects of technological change on labour markets.[1] Whether in the form of industrial robots or artificial intelligence, technological progress allows firms to automate more and more tasks, replacing workers with advanced technological tools. Following the terminology of Acemoglu and Restrepo (2019), automation results in declining employment (displacement effect), which can be compensated, or even more than compensated, by a higher demand for labour in non-automated tasks (productivity effect), but also by the creation of completely new tasks in which labour has a comparative advantage (reinstatement effect). Thus, although some workers might be expelled from the labour market, others can be re-employed in non-automated tasks. While it is well documented that workers losing their job in plant closures or mass layoffs suffer significant and enduring employment and wage losses (Couch and Placzek, 2010; Huttunen, Møen, et al., 2018), less is known about the effect of robot exposure. Several studies, such as Acemoglu and Restrepo (2020) and Dauth et al. (2021), focused on the overall adjustment of the (local) labour market. Our work proposes an alternative perspective by investigating the reallocation process following the introduction of robots and focusing on the *quality* of the new jobs found by displaced workers.

Besides the potential for job destruction and workers' reallocation, a peculiar characteristic of the automation process is that it encompasses important redistributional consequences. This is because the bulk of the losses, both in terms of employment and wages, are suffered by middle- and low-skilled workers, while the high-skilled are complemented by these new technologies and, therefore, enjoy higher wages and increased demand (Blanas et al., 2019; Autor and Dorn, 2013). Furthermore, although it is true that technological progress does not only result in the automation of human labour, but also in the creation of completely new tasks and occupations, these are mostly performed by high-skilled workers (Moll et al., 2021; Arntz et al., 2020). Concerns over potential negative effects on the middle- and low-skilled are often dismissed with the claim that displaced workers are not permanently excluded from the production process but just reallocated to other tasks, occupations or sectors (Nakamura and Zeira, 2018). Indeed, several studies showed that declining manufacturing employment is compensated, or even more than compensated, by service sector job growth (Mann and Püttmann, 2021; Dauth et al., 2021). When just focusing on pure employment levels, this might strike as a reassuring outcome. However, the same does not hold from a welfare-oriented perspective, as these jobs might be offering lower pay and worse employment security (Korchowiec, 2019). On top of exacerbating inequality among skill groups, automation shocks have the potential for widening regional

[1]For example, Pratt (2015) has warned about a possible "Cambrian explosion" for robotics, which, by taking place in a much larger proportion and shorter time than previous waves of new technologies, has the potential to displace a larger proportion of the workforce. Similarly, Frey and Osborne (2017) estimated about 47% of total US employment to be at high risk of automation over the next one or two decades.

divergence through the geographic mismatch in job creation and job destruction: while most jobs are destroyed in production-intensive manufacturing hubs, new jobs are created in service-intensive cities and regions, which benefit from robot-induced lower production costs (Acemoglu and Restrepo, 2020).

While curbing automation in an effort to protect employment can lead to missed growth opportunities, crippled competitiveness and inability to keep up with international competitors (Aghion, Antonin, et al., 2020; Humlum, 2019; Mitchell and Brynjolfsson, 2017), failure to address the needs of the "losers" with adequate policies can result in a number of individual and social problems. Several studies documented the impact of job loss on mortality (Browning and Heinesen, 2012; Sullivan and Wachter, 2009), depression (Riumallo-Herl et al., 2014), cardiovascular diseases (Noelke and Avendano, 2015), life satisfaction (Aghion, Akcigit, et al., 2016), and fertility (Huttunen and Kellokumpu, 2016). Furthermore, although only some categories of workers are directly affected by automation shocks, the expectation of a likely reduction in income and lower job prospects result in a feeling of uncertainty that can spread to the whole community (Florida, 2017; Moretti, 2012). As it became clear with Brexit in the UK but also with Trump's victory in the US, perceived economic decline, feelings of abandonment from the institutions and mounting discontent concentrated within specific social groups or regions can have far-reaching consequences for the whole society, as they facilitate the rise of populist and far-right forces (McCann, 2018; Los et al., 2017; N. Lee et al., 2018; Kurer, 2020). In this sense, given the strong spatial dimension of automation (Autor, Dorn, and Hanson, 2013b; Leigh and B. R. Kraft, 2018), industrial robots can be thought as being one of the factors contributing to the emergence of a geography of discontent (Dijkstra et al., 2020) and triggering the so-called "revenge of places that don't matter" (Rodríguez-Pose, 2018). Indeed, there is empirical evidence of the relation between industrial robots and unhappiness (Hinks, 2021), decreased relative marriage-market value of men (Anelli, Giuntella, et al., 2021), and populist or far-right voting (Milner, 2021; Petrova et al., 2021; Caselli et al., 2020; Anelli, Colantone, et al., 2021; Frey, Berger, et al., 2018).

Solid and thorough empirical evidence is thus essential to exploit the full potential of new technologies while protecting the most vulnerable workers and regions with adequate policies. Due to the lack of suitable microdata, most of the existing studies evaluating the effect of technological change on labour market outcomes rely on aggregated measures, either at the country, region or industry level. However, this approach might provide biased results, as automation changes the composition of employed workers (Grigoli et al., 2020). Besides, the negative effects for some specific groups of workers might be overlooked, leading to inappropriate policy response (Raj and Seamans, 2019; Beraja and Zorzi, 2021; Kurer and Gallego, 2019). This study contributes bridging these gaps by shedding some light on two aspects which are often neglected by studies on automation. The first aspect we address is the *quality* of the reallocation process in the short- and medium-term for *displaced* workers, i.e. workers who are dismissed by their employers.[2] Workers employed in sectors with a high density of industrial robots might be displaced for two reasons. To begin with, they might be employed in firms which adopt robots and therefore replace production workers with a more skilled labour force (Bonfiglioli, Crinò, Fadinger, et al., 2020; Humlum, 2019). Alternatively, they might work in non-adopting firms, which cannot compete with the increase in productivity of robot-adopting competitors and are eventually crowded out of the market (Koch et al., 2021; Acemoglu, LeLarge, et al., 2020). While quite some attention has been devoted to whether displaced workers get re-employed or not, little has been said about the quality of the new match. There are many factors which might cripple workers' re-employment prospects. First, a shift of the labour demand towards workers with higher or new skills (Koch et al., 2021; Humlum, 2019). Second, geographic mismatch between automation-induced job destruction and creation (Acemoglu and Restrepo, 2020). Third, reallocation frictions between sectors (D. Lee and Wolpin, 2006). Therefore, the first question we tackle is:

Q1: Do automation-exposed displaced workers get reallocated to jobs of lower quality?

While other studies, such as Dauth et al. (2021) and Dottori (2021), addressed this question by looking at employment and earnings prospects over the long run, we explore several dimensions of job-quality: earnings, qualification level, employment security (permanent or temporary contract) and type of employment ("regular" or through a temporary employment agency). Considering other aspects of job quality, especially those related to employment security, is important to try capturing not only worker's material well-being but also factors able to trigger feelings of economic insecurity and status decline, which are strong predictors of social and political discontent (Kurer, 2020; Gingrich, 2019).

The second aspect we contribute to is the investigation of the effectiveness of reallocation, to a different sector or local labour market, as an adjustment mechanism. Acemoglu and Restrepo (2020) show that, due to trade links, the negative employment effect in robot-intensive US commuting zones was at least partly compensated by employment and wages' expansion in other areas, which could benefit from robot-induced lower production costs. Standard economic theory would then expect dismissed workers from automation intensive areas to migrate to better performing labour markets. Indeed, vigorous labour mobility in response to regional utility differentials is a widespread assumption in regional and urban economics (Rodríguez-Pose, 2018;

[2]The rich dataset we employ allows us to see the reason for termination of each work spell and we focus on spells reporting the code "54 - Baja no voluntaria" ("54 - Non-voluntary leave").

Kline and Moretti, 2014). Similarly, displaced workers struggling to find a new occupation in the same sector are expected to relocate to a sector with a lower exposure to industrial robots, assuming that new jobs are created there through either the productivity or the reinstatement effect. However, the outcome of sectoral and regional reallocation is not obvious. On the one hand, relocating might provide access to better opportunities and higher wages. On the other hand, if the worse outcomes are due to the shift of manufacturing labour demand towards more skilled workforce or to the impossibility of transferring sector-specific skills to new occupations, the benefits of relocation might be disappointing. Hence, the second question we address is:

Q2: Is reallocation to a different sector or local labour market an effective adjustment mechanism for automation-exposed displaced workers?

The study focuses on the Spanish case for three reasons. First, Spain is among the developed countries with the highest robot density (IFR, 2018) but not a leading one, such as Germany (investigated in Dauth et al., 2021). Therefore, the analysis of the Spanish case might provide new knowledge that can be translated to a wider list of countries. Second, although there is some evidence that automation negatively affected some categories of Spanish workers (Koch et al., 2021), little is known on whether and how they were reabsorbed by the economic system. Finally, it is documented that Spanish workers are somehow sensitive to economic factors when it comes to internal migration choices (Melguizo and Royuela, 2020). Therefore, it is an interesting setting to investigate whether internal migration also played a role in alleviating adverse effects for automation-displaced workers.

What emerges from our empirical analysis is a non-negligible negative impact for middle- and low-skilled exposed workers. Six months after displacement these workers are still more likely to be unemployed and have a higher probability of experiencing a fragmented work-life, with multiple contracts and fewer days worked. Among those who find a new occupation, workers displaced from sectors with an increasing density of industrial robots have a higher probability of being re-employed in jobs offering a lower pay. The pay differential might be explained by the fact that exposed workers are more likely to end up in jobs requiring a lower qualification. Furthermore, they have a higher probability of being re-employed by temporary-employment agencies. Relocation to different sectors or local labour markets does not offer any sort of advantage, if anything, those who switch sector have an even higher probability of getting a lower-paid job. Some categories of middle- and low-skilled workers who stay employed in sectors and regions more exposed to robots seem to enjoy part of the benefits stemming from automation. In particular, those with a permanent contract in the previous job are less likely to switch to a temporary one. The great majority of negative effects for less skilled workers are not purely short-term but persist up to 36 months. In general, high-skilled workers are less negatively affected by exposure, although they also incur a penalty when changing sector. All in all, our results suggest that active labour market policies, such as re-training, might be necessary to help automation-displaced workers transition to a new job of similar quality as the previous one. We suggest policies aimed at turning "losers" into "winners" rather than pure compensatory policies, as automation threatens both the material well-being and social status of exposed workers, but the latter is the one pushing them towards populist parties (Kurer, 2020; Gingrich, 2019).

In addition to the papers we have mentioned, this work is also related to the empirical literature on employment polarization (Autor, Levy, et al., 2003; Fernández-Macías, 2012), wage inequality (Van Reenen, 2011), the scarring effect of unemployment spells (Clark et al., 2001), job satisfaction (Green, 2007), job quality after displacement (Lalive, 2007), migration (Basso et al., 2020; Boman, 2011) and agglomeration economies (Duranton and Puga, 2004).

The remainder of this paper is organized as follows. Section 2 presents a short literature review, Section 3 describes the data, and Section 4 discusses the empirical approach. Section 5 presents the results, while Section 6 and Section 7 introduce and discuss the heterogeneity analysis and robustness checks, respectively. Finally, Section 8 concludes.

2 Literature Review

Any restructuring of firms and labour markets generally involves benefits for many, but significant losses for those who are displaced. As highlighted above, there is a long list of personal and social drawbacks associated to job loss. When looking at labour market outcomes, the evidence for the US shows that job displacement has detrimental long-term effects on earnings (Couch and Placzek, 2010; Stevens, 1997; Jacobson et al., 1993; Ruhm, 1991), while the existing evidence for Europe is less conclusive: Gregory and Jukes (2001) and Huttunen, Møen, et al. (2011) found negligible effects, whereas other works, such as Eliason and Storrie (2006), detected significant and negative effects for both employment and earnings.

Automation-induced restructuring has the potential to generate large job losses but it can also create new job opportunities, thanks to an increase in overall productivity. Although task-based models (Acemoglu and Restrepo, 2020; Acemoglu and Restrepo, 2019; Nakamura and Zeira, 2018) offer a handy conceptual framework when studying the relation between technological change, employment, and wages, the net effect of automation on these outcomes ultimately remains an empirical question. This is because, as theorised by these same models, the final outcome depends on the equilibrium among a number of forces, such as displacement, productivity, reinstatement, and composition effects (Acemoglu and Restrepo, 2020; Acemoglu and Restrepo, 2019). Furthermore, automation's impact is mediated by a series of context-specific factors, including local labour market institutions (Dauth et al., 2021), workforce age structure (Humlum, 2019), off-shoring intensity (Bonfiglioli, Crinò, Gancia, et al., 2021), the share of replaceable tasks (Bonfiglioli, Crinò, Fadinger, et al., 2020) and the degree of exposure to international competition (Aghion, Antonin, et al., 2020). Therefore, it is perhaps not surprising that, even when focusing on a very specific subset of automation technology, i.e. industrial robots, the empirical evidence on its effect on employment is heterogeneous.

In general, cross-industry studies did not detect a net negative impact of automation on employment: Graetz and Michaels (2018) found no effect at all, while Klenert et al. (2020) and Aghion, Antonin, et al. (2020) even estimated a positive impact.[3] However, the industry-level approach might be limiting, as greater use of robots in an industry can benefit the rest of the economy through lower prices and increased productivity, thereby expanding employment in other industries. To keep these spillovers into account, other studies analysed the effect of robot adoption at the (local) labour market level. Acemoglu and Restrepo (2020) documented a strongly negative effect of robots on net employment in the US, as employment expansion in less automated commuting zones was not enough to compensate for the large displacement effect in robot-adopting ones.[4] These results were confirmed by Bonfiglioli, Crinò, Gancia, et al. (2021) using a more detailed dataset on robots and factoring in the role of off-shoring. What emerged from their analysis is that automation contributed to the re-shoring of economic activity in the US, which mitigated but did not fully compensate the large displacement effect caused by robots. On the contrary, Dauth et al. (2021) found no effect on total employment at the local level in Germany, as employment expansion in services was enough to offset the displacement effect in manufacturing. Similar conclusions were reached by Dottori (2021) for the Italian case.

The majority of firm-level studies found a positive relation between robot adoption and employment (Aghion, Antonin, et al., 2020; Acemoglu, LeLarge, et al., 2020; Dixon et al., 2021).[5] Furthermore, robot adoption seems to be followed by sizeable increases in productivity (Bonfiglioli, Crinò, Fadinger, et al., 2020; Aghion, Antonin, et al., 2020; Acemoglu, LeLarge, et al., 2020), which is consistent with employment expansion for adopters generally coming at the

[3] Note that Klenert et al. (2020) use a simple OLS which might be confounded by positive demand effects influencing both employment and robot adoption.

[4] Also Leigh, B. Kraft, et al. (2020) analysed the US and found a positive effect of robot adoption on local employment level. The discrepancy of these results might be explained by several factors. First, they relied on simple OLS rather than using IV techniques to purge from demand and other confounding shocks. Second, instead of adopting commuting zones as labour market boundaries, they focused on US Census-defined core-based statistical areas (CBSAs) which are less representative of actual labour markets. Third, they analysed the post-recession period (2010-2016), while Acemoglu and Restrepo (2020) cover the pre-recession period (1990-2007).

[5] A notable exception is represented by Bonfiglioli, Crinò, Fadinger, et al. (2020) who found that, although demand shocks result in a spurious positive correlation between robot imports and employment, robot adoption is followed by a fall in demand for less skilled labour force, as the demand shifts towards high-skill professions.

expenses of non-adopters (Koch et al., 2021; Acemoglu, LeLarge, et al., 2020). Interestingly, even within adopting firms the advantages of automation are not passed to all workers equally. Humlum (2019) found that adopters lay-off production workers to hire more skilled workers. Similarly, Acemoglu, LeLarge, et al. (2020) and Bonfiglioli, Crinò, Fadinger, et al. (2020) detected a labour demand shift towards a more skilled labour force. On the contrary, Aghion, Antonin, et al. (2020) and Koch et al. (2021) documented an increase in employment also for low-skilled workers, even if not as pronounced as the one for the more skilled. In terms of wages, Aghion, Antonin, et al. (2020) found no effect, while Koch et al. (2021) detected a decline in labour share and Humlum (2019) estimated an increase in wages for high-skilled workers but a decline for production workers.

Evidence regarding the effect of robots and automation on individual workers' outcomes is much less abundant. In general, despite the lively debate over robots' impact on net employment, there seems to be some consensus on the idea that at least part of the displaced workers gets reallocated to other occupations, firms or sectors (Dauth et al., 2021; Mann and Püttmann, 2021). Yet, only a very limited number of studies addressed the fact that these jobs might be of lower quality, offering lower pay and worse employment security. Korchowiec (2019) investigated the impact of industrial robots on occupational mobility in the US and found that exposed workers were more likely to switch occupation and the probability of switching was higher at the bottom of the wage distribution. Cortes (2016) found evidence of selection on ability for workers switching out of routine jobs, with the low-ability ones being more likely to move to lower-paying non-routine manual occupations.[6] Finally, Dauth et al. (2021) followed a sample of German workers employed in manufacturing in 1994 for the subsequent 20 years. They detected a positive effect of industrial robots on earnings for workers who switched occupation within the same establishment, but significant losses for those who were displaced, either switching industry or leaving manufacturing altogether. Using a similar approach, Dottori (2021) found comparable results for Italy, with an overall positive but small employment effect for incumbent manufacturing workers, conditional on remaining at the original firm.

To our knowledge, no work specifically focused on the losers, i.e. displaced workers, and on the effectiveness of the adjustment mechanisms they adopt. A close paper to ours is the one from Huttunen, Møen, et al. (2018), looking at the impact of job loss on regional mobility in Norway. The authors considered displaced workers as the treatment group, being the control group all workers who were not displaced, and found that regional mobility was not always an effective coping strategy, as those who moved to places where they had family or to rural areas faced large

[6] Workers employed in routine jobs are generally considered as the most exposed to automation shocks, as their tasks can be easily automated (Autor and Dorn, 2013).

income losses. Czaller et al. (2021) investigated the role of urbanisation in mitigating automation risk through occupational mobility in Sweden and found that moving to larger regions was a good adaptation strategy but only for some groups, as the benefits varied depending on gender, migration status and education. In our work we focus only on displaced workers, inspecting whether exposure to robots pushes them towards jobs of lower quality and assessing whether sector or spatial mobility are adequate coping strategies after job loss.

3 Data and Descriptive statistics

Worker-level information is taken from the *Muestra continua de vidas laborales* (MCVL), an anonymised panel extracted from the Spanish Social Security records. The dataset comprises 4% of the reference population, roughly amounting to one million individuals, and provides reliable information on each subject, including age, province of birth, gender, province of first job and current place of residence. Furthermore, a very detailed set of characteristics is reported for every work and unemployment spell, such as date of start and termination, *cause for termination of the contract*, province of work, economic sector, earnings, type of contract, and number of workers employed in the same firm. It shall be noted that, although the MCVL allows to retrieve the whole labour history of each worker included in the sample, it is only representative of the population registered in the Social Security system in the years of reference, i.e. the period 2004-2019. However, assuming the composition of the labour market does not change drastically from one year to next few ones, we enlarged our observation window by three years, back until 2001. Moving back the starting point to gain even a few years is important as the employment in manufacturing fell dramatically in Spain during the early 2000s (see Figure 1). Due to the unavailability of a few control variables for the most recent years, our final dataset covers displacements occurring between 2001 and 2017.

We extract our measure of automation exposure from the International Federation of Robots' dataset (IFR), which is based on surveys of robot suppliers and covers roughly 90% of the industrial robots' market. The dataset reports the stock of robots by country, industry, and year for the period 1993-2018.[7] The IFR dataset adopts the NACE Rev.2 classification for economic sectors. However, the IFR codes do not match perfectly the NACE ones, as several categories with few robots are aggregated together, while those with many robots (such as automotive) are

[7] In fact, for some country-sector pairs data start later. For our analysis we need robot data for the period 1999-2016. For Spain one sector ("35-39") has data starting from 2002, four sectors ("01-03", "05-09", "19-21" and "22") from 2004 and one ("22") from 2007. Given that this issue concerns five sectors out of the 19 we consider and that three of them are non-manufacturing (hence they involve few robots anyway), we prefer setting the number of robots to zero for these sector-year pairs and still start our analysis from 2001, as the early 2000s are particularly interesting when studying displacement from manufacturing sectors. Table A1 in the appendix reports the year of start by sector for Spain and the countries we use (or considered using) as instruments.

more disaggregated. Table 1 reports the aggregation strategies we employ in the study to merge IFR data with sector codes included in the MCVL. The baseline aggregation scheme includes 19 categories. It shall be noted that a non-negligible share of robots is included in the IFR "unspecified" classes. There are two reasons why a robot might be included in one of these categories. First, robot suppliers also use "unspecified" classes to report robots for which they do not know the exact destination sector. Second, being an industry association, the IFR has to comply with antitrust regulations. This implies that it is not allowed to reveal a number if it does not contain data from at least four independent companies. If a data point is non-compliant, the IFR reclassifies it to "unspecified" and reports "0" in the original cell. Note that these robots are still included in the upper-level stock. For instance, robots assigned to the category "279 - Electrical/electronics unspecified" are included in "26-27 - Electrical/electronics" and in "D - Manufacturing". In this sense, there is a trade-off between precision and the number of categories we can exploit for identification. Finally, we exclude residual categories "90 - All other non-manufacturing branches", "91 - All other manufacturing branches" and "99 - Unspecified" from all aggregation schemes, as it is not possible to assign their robots to any specific sector.

Secondary data sources are: (1) *Instituto Nacional de Estadistica* (INE), from which we take the number of employees by sector in 1995; (2) EU-KLEMS (version 2017) from which we take investments in information and communication technologies (ICT); (3) UN-Comtrade, from which we take imports from China; (4) Eurostat, from which we retrieve the Harmonised Index of Consumer Prices (2015 = 100).

3.1 Earnings, education and sample restriction

Our measure of labour earnings derives from the base used to calculate Social Security contributions. This corresponds to monthly labour earnings excluding other compensation payments (e.g. extra hours, death or dismissal compensations, travel and other expenses). For employees, this generally coincides with the actual average monthly remuneration, while it may not be the case for self-employed workers and workers registered with special regimes or special agreements (Seguridad Social, 2021). Contribution bases are top and bottom-censored, with maximum and minimum caps varying over time and across occupation groups, also following the evolution of the minimum wage and the inflation rate. We deflate earnings using Eurostat Harmonised Index of Consumer Prices with base 2015 and compute daily wages as the ratio between the monthly contribution base and the number of "effective" days worked in that specific month. Effective days are computed as the product between the number of natural working days and the part-time coefficient.[8] For each transition analysed, we look at two measures of earnings:

[8]The MCVL does not report the number of hours worked so we are not able to compute exact hourly wages. However, the panel includes a "part-time coefficient", which indicates the hours worked by the employee as a fraction, expressed

the mode of the earnings in the last 12 months before termination of the old job and the mode of the earnings in the first 12 months of the new job. If a job lasts $n < 12$ months, we take the mode in the n months. Rather than using contribution bases, we could extract earnings from tax records. There are three main reasons why we prefer contribution bases to tax records. First, tax files are only available for the year of reference, hence we could not go back to 2001. Second, they are unavailable for many spells, as there are several exceptions to employment incomes that must be included in the tax return. Third, they are not available for the Basque Country and Navarra, which had high shares of employment in manufacturing and are therefore of particular interest for this analysis.

Since educational level records reported in the MCVL are not reliable, we divide workers into two skill groups based on the contribution category assigned by the Social Security to their previous job. Following De la Roca and Puga (2017) we consider five skill groups: (1) Very-high-skilled: "Engineers, graduates and senior management"; (2) High-skilled: "Technical engineers, technicians and assistants" and "Administrative and workshop managers"; (3) Medium-high-skilled: "Non-graduate assistants", "Administrative officers" and "Subordinates"; (4) Medium-low-skilled: "Administrative assistants", "First and second officers" and "Third officers and specialists"; (5) Low-skilled: "Unskilled (over 18)". We then categorise workers whose previous occupation was in the first three groups as high-skilled (HS), while the last two groups are coded as middle- and low-skilled (MLS).

As for the sample restriction, we focus only on transitions to different employers following involuntary dismissals.[9] In this, our approach differs from Huttunen, Møen, et al. (2018), as they use displaced workers as treatment group, being the control group all non-displaced workers. We also differ from Dauth et al. (2021), as they look at changes in employer, but they do not restrict the analysis to involuntary dismissals, and consequently they analyse global adjustments to the rise of industrial robots. Since displaced workers differ both from those who stay and from those who leave voluntarily, we believe that restricting the analysis only to those who face a non-voluntary leave reduces the risk to overlook the losses of the losers because they get covered by the gains of the winners. Next, we exclude all transitions to/from self-employment, because contribution bases for self-employed might differ greatly from the true labour-earnings, and we drop transition to/from spells whose daily earnings exceed the maximum base or are below the minimum base imposed by the Social Security. Furthermore, we drop very short spells ($<$ 30 days) and transitions to/from spells with missing or invalid information in any of the variables

in thousandths, of the usual full working day in the company. We assume a regular working day of 8 hours and adjust the monthly number of hours worked accordingly.

[9]The MCVL reports the reason of termination of the contract and we retain only transitions from jobs with a dismissal coded as "*54 - Baja no voluntaria*" ("54 - Non-voluntary leave") by the Spanish Social Security.

included in the regression. Finally, we only consider individuals aged between 18 and 60 and we drop the top 1% individuals by number of spells for computational reasons.

3.2 Descriptive statistics

Table 2 provides a descriptive overview of the estimation sample. About 42% of the transitions are to a job with a lower pay and the majority are related to temporary contracts, especially for the MLS.[10,11] Almost half of all transitions involve a change of 1-digit sector, while the share of transitions to a different province is quite lower: 15.6% for the MLS and 21.7% for the HS. The high-skilled are significantly more likely to transition to a job with a lower qualification. As for the correlation with the main dependent variable, the probability of transitioning to a job with a lower pay is higher for those changing sector, for contracts starting during the Great Recession, for temporary contracts, and for transitions from manufacturing.[12]

Figure 2 plots the flows across all 1-digit sectors (left panel) and within manufacturing (right panel). About 60% of the flows from "C - Manufacturing" are directed to other sectors. Among them, the ones receiving the largest flows are "N-Administrative and Support Service Activities" (13.20%), "G - Wholesale and retail trade" (13.05%) and "F - Construction" (12.31%). Quite worryingly, a large number (8.5%) of workers displaced from manufacturing end up in sector N's subsection "782 - Temporary employment agency activities".[13] The percentage of workers flowing into "N-Administrative and Support Service Activities" is the highest in sectors with high robot density, i.e. "29 - Automotive" (24.62%) and "22-Rubber" (20.97%). Interestingly, a large fraction of the flows from "N - Administrative and Support Service Activities" are also towards "C - Manufacturing" (11.78%) and "G - Wholesale and retail trade" (12.49%), suggesting that, at least for some workers, the permanence in temporary employment agencies might be just transitory. From the left panel of Figure 2 it emerges that workers who find a new job in manufacturing mostly remain the same 2-digit sector. Geographic relocation appears to be far less common than sectoral one and is less correlated with a worse pay. From Figure 3 it is clear that most of the transitions occur within the same province or between provinces of the same *Comunidad Autonoma*. Notable exceptions are the flows to/from Madrid and Barcelona.

[10]We compare the mode of earnings in the last 12 months before termination of the old job and the mode in the first 12 months of the new job.

[11]Since we focus on involuntary dismissals, temporary contracts tend to be overrepresented in our sample, as these contracts have lower termination costs. Still, Spain is the EU country with the highest share of temporary employment. At the beginning of our observation period, i.e. 2001, 32.2% of total dependent employment was temporary, against an EU27 average of 13.4% (OECD, 2021).

[12]Interested readers can find a balancing analysis in Table A2 of the appendix.

[13]Workers employed through temporary employeemnt agencies have been found to experience worse working conditions and receive lower compensation and less training than employees with a standard employment contract (Nienhüser and Matiaske, 2006).

4 Empirical Approach

The focus of the analysis is on individuals who are involuntarily dismissed at least once in the observation window, i.e. the period between 2001 and 2016. Then, for every transition i of a worker w previously employed in sector s, being dismissed at time t and finding a new job at time τ, the equation of interest is:

$$\begin{aligned} Y_{wist\tau} = {} & c + \beta \cdot \Delta Exp_{s,t-1} + \pi \cdot \Delta Trade_{s,t-1} + \mu \cdot \Delta ICT_{s,t-1} + \\ & \boldsymbol{\Omega_0} \cdot \boldsymbol{X_{i,\tau}} + \eta_0 \cdot \theta_\tau + \lambda_0 \cdot NUTS2_{i,t} + \psi_0 \cdot Sector_{i,t} + \varphi_0 \cdot Contract_{i,t} + \\ & \kappa \cdot \Delta NUTS3_i + \nu \cdot \Delta Sector_i + \iota \cdot \Xi_w + \epsilon_{wist\tau} \end{aligned} \tag{1}$$

Dependent variables and skill groups

Five different outcomes $Y_{wist\tau}$ are considered: (a) a binary indicator capturing whether the new job offers a lower daily pay than the previous one; (b) the ratio ($\times 100$) of the current pay over the previous one; (c) a dummy for whether the current job requires a lower qualification than the previous one;[14] (d) a dummy for whether the new job is with a temporary contract (restricting the sample to transitions from jobs with a permanent contract); (e) a dummy for whether the new occupation is in a temporary employment agency ("*Empresa de trabajo temporal*", ETT). As we expect the effect of robot exposure to vary greatly across skill groups, we perform all regressions separately for high-skilled and middle- and low-skilled.

Exposure to robots

The change in exposure to industrial robots is measured as:

$$\Delta Exp_{s,t-1} = \frac{robots_{s,t-1} - robots_{s,t-2}}{employment_{s,1995}} \tag{2}$$

For every sector s, $robots_{s,t-1}$ ($robots_{s,t-2}$) is the total stock of robots in year $t-1$ ($t-2$), with t being the year the worker is displaced, while $employment_{s,1995}$ captures the sector size in 1995, measured in thousands of workers. Figure 4 reports the variation in robots' adoption in Spain by sector and year: the great majority of installations are in manufacturing, especially in the automotive sector, and there is a strong cyclical component, with lower values during the Great Recession.

Clearly, robot adoption is not an exogenous random shock. Although NUTS3 region and broad sector fixed effects could purge certain trends, it cannot be excluded that the coefficient of

[14] This variable is *not* based on the 2-group skill variable ("1: High-skilled", "2: middle- and low- skilled") but rather on the 5-group variable ("1: Very-high-skilled", "2: High-skilled", "3 - Medium-high-skilled", "4 - Medium-low-skilled", "5 - Low-skilled"). Hence, a person can transition from a high-skilled to another high-skilled job, but still have a skill-downgrading (e.g. from "1 - Very-high-skilled" to "2 - High-skilled" or to "3 - Medium-high-skilled").

interest, namely the one of $\Delta Exp_{s,t-1}$, only captures the causal effect of robots when there are no parallel confounding unobservable shocks affecting both robot installations and labour market outcomes. To address this concern, we adopt an instrumental variable approach similar to the one used in Autor, Dorn, and Hanson (2013a), Acemoglu and Restrepo (2020) and Dauth et al. (2021): industry level robot adoption in Spain is instrumented with robot installations across industries in other European countries. More precisely, we average over Germany, France, Italy, and the United Kingdom.[15] In this way, we try to capture robot adoption induced by exogenous improvements in technology and by the necessity to keep up with international competitors.

The role of the adjustment mechanisms is captured by replacing $\Delta Exp_{s,t-1}$ with its interaction with a binary indicator for sectoral or geographic relocation, i.e. $\Delta Exp_{s,t-1} \cdot \Delta NUTS3_i$ or $\Delta Exp_{s,t-1} \cdot \Delta Sector_i$, respectively.[16]

Controls

$\Delta Trade_{s,t-1}$ captures trade exposure by means of the change in net imports from China in sector s between year $t-1$ and $t-2$, while $\Delta ICT_{s,t-1}$ controls for investment in information and communication technologies (ICT), namely the change in real fixed capital stock per worker for ICT equipment in the same period. $\boldsymbol{X_{i,\tau}}$ is a matrix of basic worker-spell characteristics: gender, country of birth, age on the day of start of the new job and length of the unemployment spell.[17] θ_τ is a set of fixed effects for the year in which the the new job starts. $NUTS2_{i,t}$, $Sector_{i,t}$ and $Contract_{i,t}$ are sets of fixed effects referring to the previous job: NUTS2 region, 1-digit industry and type of contract, i.e. permanent or temporary.Finally, $\Delta NUTS3_i$ and $\Delta Sector_i$ are binary indicators for whether the new job is in a different 1-digit sector or NUTS3 area than the previous one.

Unobserved ability

Despite the socio-economic controls included in the regression, individuals might still differ in their unobserved characteristics. To deal with this issue, we use a two-steps procedure. First, for every

[15] We chose these countries as they have robot data for the whole period of interest and they have similar socio-economic characteristics as Spain. As alternatives, among the countries that have available data for the whole period of interest, we also considered a group of small Nordic countries (Norway, Finland, Sweden and Denmark), the US or Japan. Figure A1 in the appendix plots the evolution of robot density across time for Spain and the instrument countries, while Table A3 reports a few first-stage statistics for the various instruments considered.

[16] We proxy local labour markets with Spanish provinces (NUTS3). This choice is not uncommon, see Melguizo and Royuela (2020) and Diaz-Serrano and Nilsson (2020).

[17] We consider five categories for country of birth: "Spain", "Center and South America", "EU28", "Africa" and "Other". In a few cases country of birth is missing while nationality is available. For these individuals we proxy the country of birth with the nationality.

job j held by worker w we estimate the following Mincerian wage regression:

$$\begin{aligned} ln(earning_{wj}) = &\ \alpha + \Xi \cdot \zeta_w + \kappa \cdot Sex_w + \delta \cdot CoBirth_w + \\ &\pi \cdot Age_{wj} + \sigma \cdot Unempl_{wj} + \xi \cdot Tenure_{wj} + \\ &\varphi \cdot Skill_{wj} + \omega \cdot FullPart_{wj} + \nu \cdot Stab_{wj} + \rho \cdot YearStart_{wj} + \\ &\mu \cdot Sector_j + \lambda \cdot NUTS3_j + \psi \cdot NumWorkers_j + \epsilon_{wj} \end{aligned} \tag{3}$$

The dependent variable $ln(earning_{wj})$ is the natural logarithm of job's earnings. For each job we use the mode of daily earnings in the last 12 months before termination. ζ_w, Sex_w and $CoBirth_w$ are worker-specific categorical variables capturing the worker's fixed effect, gender and country of birth, respectively. Age_{wj}, $Unempl_{wj}$ and $Tenure_{wj}$ are continuous worker-job controls: age at the beginning of the job, number of weeks unemployed between this spell and the previous one and total number of days in the job. $Skill_{wj}$, $FullPart_{wj}$, $Stab_{wj}$ and $YearStart_{wj}$ are categorical worker-job controls: skill group, a binary indicator for whether the job is full-time (*vs.* part time), a binary indicator for the type of contract, i.e. permanent *vs.* temporary and a set of fixed effects for the year of start of the job. Finally, $NUTS3_j$ and $Sector_j$ are sets of fixed effects for NUTS3 region and 2-digit industry, respectively, while $NumWorkers_j$ is a control for the number of workers employed in the firm. Note that, for estimating this regression, we use each worker's whole working history (without restricting our sample to the 2001-2016 window) but we only keep spells which are at least 30 days long. The individual parameter (Ξ) associated every worker fixed effect ζ_w should capture workers' unobserved ability. Therefore, the second step of the procedure is to include Ξ as an additional control in Equation 1.

4.1 Medium-term effects

The baseline analysis compares each job to the one coming immediately after. In this sense, it looks at the short-term effect of automation exposure on displaced workers. Arguably, any effect estimated by the baseline model, be it positive or negative, might be just a temporary condition and the worker might converge back to the previous condition in the medium- to long-term. To investigate this hypothesis, we adopt the same approach as in Equation 1 but, rather than looking at workers' next job, we consider their condition after n months, with $n \in \{3, 6, 12, 24, 36\}$.[18] For this analysis we also consider some additional outcomes: (1) a dummy for being working (either as employee or as self-employed); (2) a dummy for being unemployed (with benefits); (3) a dummy for being out of the Social Security records (i.e. unemployed without benefits or out of the labour force or working out of Spain); (4) the number of different contracts since dismissal; (5) the number

[18]If the worker has more than one job in month n we consider the one providing the highest total earnings. In case of ties, we then take the the one lasting longer and then the one ending later.

of different employers since dismissal; (6) the number of effective days worked in the n-th month; (7) a dummy for having lower total earnings (i.e. summing up work earnings and Social Security contributions); (8) the ratio of total earnings in month n over the month before dismissal. In this way we hope to get a more complete picture of workers' condition in the medium run, not just in terms of earnings but also of employment stability.

5 Results

This section presents and discusses the empirical results for the short-term (Section 5.1) and for the medium-term (Section 5.2)

5.1 Short-term

As we have seen in Section 3, a large share of displaced workers faces a worse pay in the new job. We analyse the impact of job displacement using the specification of Equation 1 and we report the results of our regressions in Figure 5. The dependent variable in Panel 5a is a dummy for whether the new job offers a lower pay. Less-skilled workers displaced from sectors with higher exposure to robots face a higher probability of a lower-paid re-employment, compared to workers displaced from less exposed sectors. Overall, one additional robot per 1,000 workers in the sector increases their probability to end up in a lower-paid job by roughly 2.1 percentage points. The penalty is significantly higher for those whose new job is in a different sector, while migration does not seem to offer any "protection". In general, the high-skilled appear to be less affected by robot exposure. However, there is quite some heterogeneity in their outcomes depending on the adjustment mechanisms they adopt. While exposure to robots lowers the probability to get a lower-paid job for those who stay in the same sector, workers who switch suffer a significant penalty. On the contrary, there is no significant difference in the outcomes depending on geographic relocation. While a binary indicator has the advantage of clearly separating those scoring better or worse than before, a continuous measure of pay differentials allows for a better understanding of the impact of robot exposure on individuals' re-employment prospects. Therefore, Panel 5b reports the estimates for the ratio of the previous pay over the new one ($\times 100$). The results mirror the ones of the binary indicator, with exposure having a worse effect for less skilled workers and reallocation to a different sector being the worse adjustment mechanisms for both groups. However, while geographic reallocation makes no difference for high-skilled, it results in even worse outcomes for middle and low-skilled workers. This is in line with the results in Huttunen, Møen, et al. (2018), who also found that displaced movers have larger earnings drop than displaced stayers, even though movers might be positively selected. We estimate that for middle and low skilled workers the effect of one additional robot on the wage ratio ranges between -0.4 points ($\Delta Exp \cdot (\Delta Sector = 0)$) and 3.1 points ($\Delta Exp \cdot (\Delta NUTS3 = 1)$).

In a first tentative to isolate the mechanisms through which automation leads to a lower pay for displaced workers, Panel 5c looks at the effect of robot exposure on the probability of being re-employed in a job requiring a lower qualification. Despite the small coefficients, there seems to be some evidence that middle- and low-skilled exposed workers tend to downgrade in the new occupation, especially when moving to a different sector, which might explain the lower pay. No such effect is detected for high-skilled workers. Contrary to what we observed in Panel 5b for the lower pay, spatial adjustment (migration) is not significantly associated with a higher probability to be re-employed in a new job with lower qualification, while stayers do suffer such penalty.
Another dimension of job quality is employment security. Panel 5d explores whether exposed workers are more likely to be re-employed in jobs offering a less stable contract (i.e. a temporary contract), while Panel 5e investigates the probability of being re-employed in an ETT firm. As we are interested in observing whether workers are worse off than before, for Panel 5d we restrict the sample to individuals who had a permanent contract in the previous job, while for Panel 5e we only look at people who were not displaced from ETT firms. Starting from the downgrading from a permanent to a temporary contract, no effect at all is detected for high-skilled workers, while exposed middle- and low-skilled seem to be *less* likely to switch from a permanent to a temporary contract if compared to similar workers with a lower exposure. When interpreting these seemingly counter-intuitive results, it is important to highlight that the effect is driven by workers who stay in the same sector and, to a lesser extent, also in the same region. This is in line with the argument that workers who do stay employed in sectors and regions more exposed to robots enjoy part of the benefits stemming from automation. Furthermore, it shall be remarked that only a very small subgroup of medium- and low-skilled workers had a permanent contract in the first place (see Table 2). Arguably, these are workers with very specific characteristics which can at least partially explain the different impact that robot exposure has on them. As for the employment in ETT firms, exposure increases the probability of switching from a "regular" firm to an ETT one by about 1.2 percentage points for middle- and low-skilled workers, while, on average, no effect is detected for the high skilled. Contrarily to what observed for the probability of a lower pay, geographic relocation seems to offer some sort of protection from unstable employment, as exposed workers who do not move have a higher probability of being reabsorbed by an ETT firm.

5.2 Medium-term

Figure 6 reports the regression results for the medium-term analysis. Concerning the five outcomes discussed in the previous section, the main result is that the negative effects we detected in the short-term for middle- and low-skilled workers are quite persistent over time (Panel 6a - Panel 6e). The only exception is the probability of being re-employed in an ETT firm, which becomes significantly smaller as months go by (Panel 6e). Interestingly, while some undesirable effects become stronger over time, such as the lower pay for medium and low skilled workers, high skilled workers who remain in sectors with increasing robotisation enjoy even higher pays in the long period (24 months and beyond). By shifting our focus from the next occupation to the situation after n months, we can also observe how robot exposure affects workers' life in several other dimensions, such as the fragmentation of their employment history. Even more importantly, we have the chance to say something about those workers who do not find a new occupation and permanently leave the labour market. Panel 6f shows that, while there is no effect for high-skilled workers, middle- and low-skilled workers are less likely to be working (either as employees or as autonomous workers) after being displaced from a sector with an increasing density of robots. For each additional robot per 1,000 workers in the sector, the probability of being working is about 1.1 percentage points lower after 3 months and 0.8 p.p. after 6 months. It then becomes insignificant between 12 and 24 months. These dynamics are mirrored in Panel 6g, which examines how robot exposure affects the probability of receiving unemployment benefits as the only earning in month n. Once again, we observe no effect at all for high-skilled workers, while middle- and low-skilled have a higher probability within the first 3 months (1.3 percentage points) and 6 months (0.6 percentage points). Somehow reassuringly, for the middle- and low-skilled workers there is virtually no increase in the probability of being completely out of the Social Security umbrella, i.e. neither working nor receiving any sort of benefit in Spain (Panel 6h). Perhaps surprisingly, however, there is a slight increase in the probability at $n = 3$ for high-skilled workers, which already fades away after 6 months.[19] As for the employment history fragmentation, exposure to robots seems to have no effect on the number of different employers (Panel 6i) and a very small effect on the number of total contracts (Panel 6j) and on the number of effective days worked in month n (Panel 6k). As observed before, there are heterogeneous outcomes for those who manage to remain in the same sector against those who change. Middle- and low-skilled workers changing sector experience a more fragmented work-life with multiple contracts and fewer worked days, while workers who remain in the same sector have a lower number of contracts (high-skilled) or higher number of effective days worked in the month (middle- and low-skilled). Finally, Panel 6l and Panel 6m replicate Panel 6a and Panel 6b substituting earnings from the main job with total earnings in month n.[20] Even keeping into account earnings from multiple jobs and Social Security benefits, exposed middle- and low-skilled workers are still more likely to be worse off in the medium-term, while the exact opposite holds for high-skilled workers.

6 Heterogeneity

We look at heterogeneity by: (1) gender; (2) age; (3) degree of urbanisation;(4) share of manufacturing employment in 2001. The results are reported in Table 3 (lower pay and pay

[19] A possible explanation for this phenomenon is capitalisation of the unemployment benefits (Mayor et al., 2015).

[20] We trim these earnings at the 5% and 95% to make sure our results are not driven by extreme values.

ratio), Table 4 (lower skill and less security) and Table 5 (new employment in ETT).

The first result is that, in general, there are no large and significant differences across the various groups considered for high-skilled workers. On the contrary, we detect significant differences for the middle- and low-skilled workers across all four dimensions considered:

- Starting from gender, females are more negatively affected by exposure to robots than men, especially in terms of lower pay and probability of being re-employed in an ETT firm. What is particularly interesting is that less skilled women experience a negative effect on pay even when not changing sector ($\Delta Sector = 0$), while men do not. This suggests that, while men who stay employed in automating sectors enjoy some of the benefits stemming from robot adoption, women are somehow excluded from these benefits.

- Moving to the role of age, middle- and low-skilled workers younger than 40 are the ones driving the increase in the probability of skill-downgrading, with an associated lower pay ratio in some specifications.

- Regarding urbanisation, workers from urbanised areas seem to be significantly less exposed to the risk of switching from a permanent to a temporary contract, especially when changing sector.

- Finally, the overall positive effect of robots' exposure on the high-skilled pay gap is mainly driven by more manufacturing intensive areas, being such provinces the ones associated with the negative effect on pay of middle- and low-skilled workers who remain in the same sector. For these workers, territorial manufacturing specialization is also associated with higher probability of being re-employed with a temporary contract when changing sector, and in new jobs with lower qualifications.

7 Robustness checks

We perform a wide array of robustness checks to make sure that our results are not the consequence of any specific choice of variables or sub-samples. Appendix Tables A4 to A13 report the relative estimation results.

- *Sample restriction.* We tested several sub-samples: (1) keep only transitions from manufacturing; (2) for each individual, keep only the transition from her longest spell; (3) keep only transitions from spells at least 6 months long; (4) look only at transitions with at least 4 or 24 months of unemployment in-between; (5) exclude transitions from the automotive sector; (6) keep only transitions from and to jobs in the general regime; (7) consider only prime-age workers (25-55 years old); (8) consider only displacements occurring between 2006 and 2017 (i.e. the time window with complete robot data for all sectors); (9) consider only displacements occurring between 2001 and 2007 (pre-crisis); (10) consider only displacements occurring between 2008 and 2017 (post-crisis); (11) consider only spells at least 180 or 365 days long.

- *Aggregation schemes.* Since there is a trade-off between the number of IFR categories we employ and measurement error, we test the robustness of our results across different schemes of sector-aggregation for the robot density. While in the baseline specification we adopt a scheme with 19 categories, we also test schemes with 15, 17 and 20 classes (Table 1 reports the composition of each scheme).

- *Migration.* In the baseline specification we employ a migration-dummy which is equal to 1 if the new job is in a different NUTS3 area than the previous one. In this section we test a more "stringent" measure of geographic relocation, i.e. a dummy equal to 1 only if workers moves to a non-neighbouring NUTS3 area.

- *Fixed effects.* In the baseline models we include three sets of fixed effects for the previous job (NUTS2 region, 1-digit industry and type of contract, i.e. permanent or temporary) and we control for the year of start of the new job. In this section we assess the robustness of results to: (1) adding the same set of fixed effects for the previous job also for the new one; (2) adding the interaction between NUTS2 region of previous job and year of dismissal; (3) adding the interaction between NUTS2 region of new job and year of start of the new job.

- *Sector FE and ΔSec.* In the baseline specification we control for the 1-digit sector of the previous job and we include a dummy equal to one if the new job is in a different 1-digit sector than the previous one. In this section we test two more refined sector fixed effects (i.e. IFR15(1-dig) and IFR15(2-dig)), and one more refined dummy for the change of sector (i.e. ΔIFR15(2-dig)). The variable IFR15(1-dig) adopts the same aggregation reported in Table 1 for sectors with robots and the usual NACE Rev.2 1-digit aggregation for sectors without levels. Variables IFR15(2-dig) and ΔIFR15(2-dig) are constructed following the same logic but using NACE Rev.2 2-digit aggregation for sectors without robots.

Although the estimates are larger or smaller than the baseline ones depending on the specification, the main results, especially concerning the key role of the relocation to a different sector, are robust to all alternative specifications.

8 Conclusion

While quite some attention has been devoted to the impact of automation on employment levels, little has been said about the *quality* of the new match for displaced workers. This study provides empirical evidence that middle- and low-skilled Spanish workers displaced from sectors with an increasing density of industrial robots have a higher probability of being re-employed in jobs of lower quality. More precisely, they are more likely to receive a lower pay and to face less stable employment. The pay differential might be explained by the fact that they are more likely to be re-employed in jobs requiring a lower qualification. Relocation to different sectors or local labour markets does offer little to no advantage. If anything, those who switch have an even higher probability to get a worse job. However, some categories of middle- and low-skilled workers who stay employed in sectors and regions more exposed to robots enjoy part of the benefits stemming from automation. In particular, those who already had a permanent contract are less likely to switch to a temporary one. Robot exposure does not only affect workers in the short term. The majority of these effects persist for up to 36 months. Furthermore, 6 months after displacement exposed middle- and low-skilled workers are still more likely to be unemployed. Moreover, they are slightly more likely to experience a fragmented work-life, with multiple contracts and fewer days worked. In general, high-skilled workers are less negatively affected by exposure, although they also incur a penalty when changing sector. The results of the empirical analysis suggest that active labour market policies, such as re-training, might be necessary to help vulnerable automation-displaced workers transition to a new job of similar quality as the previous one.

References

Acemoglu, Daron, Claire LeLarge, and Pascual Restrepo (2020). "Competing with Robots: Firm-Level Evidence from France". *AEA Papers and Proceedings* 110, pp. 383–388. DOI: 10.1257/pandp.20201003.

Acemoglu, Daron and Pascual Restrepo (2019). "Automation and New Tasks: How Technology Displaces and Reinstates Labor". *Journal of Economic Perspectives* 33.2, pp. 3–30. DOI: 10.1257/jep.33.2.3.

— (2020). "Robots and Jobs: Evidence from US Labor Markets". *Journal of Political Economy* 128.6, pp. 2188–2244. DOI: 10.1086/705716.

Aghion, Philippe, Ufuk Akcigit, Angus Deaton, and Alexandra Roulet (2016). "Creative Destruction and Subjective Well-Being". *American Economic Review* 106.12, pp. 3869–3897. DOI: 10.1257/aer.20150338.

Aghion, Philippe, Céline Antonin, Xavier Jaravel, and Simon Bunel (2020). "What Are the Labor and Product Market Effects of Automation? New Evidence from France". *CEPR Discussion Paper 14443*.

Anelli, Massimo, Italo Colantone, and Piero Stanig (2021). "Individual vulnerability to industrial robot adoption increases support for the radical right". *Proceedings of the National Academy of Sciences* 118.47. DOI: 10.1073/pnas.2111611118.

Anelli, Massimo, Osea Giuntella, and Luca Stella (2021). "Robots, Labor Markets, and Family Behavior". *Accepted at the Journal of Human Resources*. ISSN: 1556-5068.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn (2020). "Digitalization and the Future of Work: Macroeconomic Consequences". In: *Handbook of Labor, Human Resources and Population Economics*. Ed. by K Zimmermann. 19. Springer, pp. 1–29. DOI: 10.1007/978-3-319-57365-6_11-1.

Autor, David H. and David Dorn (2013). "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market". *American Economic Review* 103.5, pp. 1553–1597. DOI: 10.1257/aer.103.5.1553.

Autor, David H., David Dorn, and Gordon H. Hanson (2013a). "The China Syndrome : Local Labor Market Effects of Import Competition in the United States". *American Economic Review* 103.6, pp. 2121–2168. DOI: 10.1257/aer.103.6.2121.

— (2013b). "The Geography of Trade and Technology Shocks in the United States". *American Economic Review: Papers & Proceedings* 103.3, pp. 220–225. DOI: 10.1257/aer.103.3.220.

Autor, David H., Frank Levy, and Richard J. Murnane (2003). "The Skill Content of Recent Technological Change : An Empirical Exploration". *Quarterly Journal of Economics* 118.4, pp. 1279–1333. DOI: 10.1162/003355303322552801.

Basso, Gaetano, Giovanni Peri, and Ahmed S. Rahman (2020). "Computerization and immigration: Theory and evidence from the United States". *Canadian Journal of Economics* 53.4, pp. 1457–1494. DOI: 10.1111/caje.12472.

Beraja, Martin and Nathan Zorzi (2021). "Inefficient Automation". *MIT Working Paper*, pp. 1–79.

Blanas, Sotiris, Gino Gancia, and Sang Yoon Lee (2019). "Who is afraid of machines?" *Economic Policy* 34.100, pp. 627–690. DOI: 10.1093/epolic/eiaa005.

Boman, Anders (2011). "Does migration pay? Earnings effects of geographic mobility following job displacement". *Journal of Population Economics* 24, pp. 1369–1384. DOI: 10.1007/s00148-010-0335-7.

Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger, and Gino Gancia (2020). "Robot Imports and Firm-Level Outcomes". *CEPR Discussion Paper 14593*.

Bonfiglioli, Alessandra, Rosario Crinò, Gino Gancia, and Ioannis Papadakis (2021). "Robots , Offshoring and Welfare". *CEPR Discussion Paper 16363*. CEPR Discussion Paper 16363.

Browning, Martin and Eskil Heinesen (2012). "Effect of job loss due to plant closure on mortality and hospitalization". *Journal of Health Economics* 31, pp. 599–616. DOI: 10.1016/j.jhealeco.2012.03.001.

Caselli, Mauro, Andrea Fracasso, and Silvio Traverso (2020). "Globalization, robotization, and electoral outcomes: Evidence from spatial regressions for Italy". *Journal of Regional Science* 61.1, pp. 86–111. DOI: 10.1111/jors.12503.

Clark, Andrew E., Yannis Georgellis, and Peter Sanfey (2001). "Scarring: The psychological impact of past unemployment". *Economica* 68.270, pp. 221–241. DOI: 10.1111/1468-0335.00243.

Cortes, Guido Matias (2016). "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data". *Journal of Labor Economics* 34.1, pp. 63–105. DOI: 10.1086/682289.

Couch, Kenneth A. and Dana W. Placzek (2010). "Earnings Losses of Displaced Workers Revisited". *American Economic Review* 100.1, pp. 572–589. DOI: 10.1257/aer.100.1.572.

Czaller, László, Rikard H. Eriksson, and Balázs Lengyel (2021). "Reducing automation risk through career mobility: Where and for whom?" *Papers in Regional Science*. DOI: 10.1111/pirs.12635.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner (2021). "The Adjustment of Labor Markets to Robots". *Journal of the European Economic Association* 00.0, pp. 1–50. DOI: 10.1093/jeea/jvab012.

De la Roca, Jorge and Diego Puga (2017). "Learning by Working in Big Cities". *Review of Economic Studies* 84.1, pp. 106–142. DOI: 10.1093/restud/rdw031.

Diaz-Serrano, Luis and William Nilsson (2020). "The regional anatomy of youths' educational attainment in Spain: The role of the employment structure in local labour markets". *Papers in Regional Science* 99.5, pp. 1487–1508. DOI: 10.1111/pirs.12540.

Dijkstra, Lewis, Hugo Poelman, and Andrés Rodríguez-Pose (2020). "The geography of EU discontent". *Regional Studies* 54.6, pp. 737–753. DOI: 10.1080/00343404.2019.1654603.

Dixon, Jay, Bryan Hong, and Lynn Wu (2021). “The Robot Revolution: Managerial and Employment Consequences for Firms”. *Management Science* 67.9, pp. 5586–5605. DOI: 10.1287/mnsc.2020.3812.

Dottori, Davide (2021). *Robots and employment: evidence from Italy*. Vol. 38, pp. 739–795. DOI: 10.1007/s40888-021-00223-x.

Duranton, Gilles and Diego Puga (2004). “Micro-Foundations of Urban Agglomeration Economies - Volume 4”. In: *Handbook of Regional and Urban Economics*. Ed. by J. Vernon Henderson and Thisse Jacques-François. Elsevier. Chap. 48, pp. 2063–2117.

Eliason, Marcus and Donald Storrie (2006). “Lasting or Latent Scars? Swedish Evidence on the Long-Term Effects of Job Displacement”. *Journal of Labor Economics* 24.4, pp. 831–856. DOI: 10.1086/506487.

Fernández-Macías, Enrique (2012). “Job Polarization in Europe? Changes in the Employment Structure and Job Quality, 1995-2007”. *Work and Occupations* 39.2, pp. 157–182. DOI: 10.1177/0730888411427078.

Florida, Richard (2017). *The new urban crisis: How our cities are increasing inequality, deepening segregation, and failing the middle class-and what we can do about it*. Hachette UK. ISBN: 0465097782.

Frey, Carl Benedikt, Thor Berger, and Chinchih Chen (2018). “Political machinery: Did robots swing the 2016 US presidential election?” *Oxford Review of Economic Policy* 34.3, pp. 418–442. DOI: 10.1093/oxrep/gry007.

Frey, Carl Benedikt and Michael A. Osborne (2017). “The future of employment: How susceptible are jobs to computerisation?” *Technological Forecasting and Social Change* 114, pp. 254–280. DOI: 10.1016/j.techfore.2016.08.019.

Gingrich, Jane (2019). “Did State Responses to Automation Matter for Voters?” *Research and Politics* 6.1. DOI: 10.1177/2053168019832745.

Graetz, Georg and Guy Michaels (2018). “Robots at work”. *Review of Economics and Statistics* 100.5, pp. 753–768. DOI: 10.1162/rest_a_00754.

Green, Francis (2007). *Demanding Work: The Paradox of Job Quality in the Affluent Economy*. Princeton University Press. ISBN: 9780691134413.

Gregory, Mary and Robert Jukes (2001). “Unemployment and subsequent earnings: Estimating scarring among British men 1984-94”. *Economic Journal* 111.475, pp. 607–625. DOI: 10.1111/1468-0297.00665.

Grigoli, Francesco, Zsoka Koczan, and Petia Topalova (2020). “Automation and labor force participation in advanced economies: Macro and micro evidence”. *European Economic Review* 126. DOI: 10.1016/j.euroecorev.2020.103443.

Hinks, Tim (2021). “Fear of Robots and Life Satisfaction”. *International Journal of Social Robotics* 13, pp. 327–340. DOI: 10.1007/s12369-020-00640-1.

Humlum, Anders (2019). “Robot Adoption and Labor Market Dynamics”. *Job Market Paper*.

Huttunen, Kristiina and Jenni Kellokumpu (2016). “The effect of job displacement on couples’ fertility decisions”. *Journal of Labor Economics* 34.2, pp. 403–442. DOI: 10.1086/683645.

Huttunen, Kristiina, Jarle Møen, and Kjell G. Salvanes (2011). “How destructive is creative destruction? effects of job loss on job mobility, withdrawal and income”. *Journal of the European Economic Association* 9.5, pp. 840–870. DOI: 10.1111/j.1542-4774.2011.01027.x.

— (2018). “Job loss and regional mobility”. *Journal of Labor Economics* 36.2, pp. 479–509. DOI: 10.1086/694587.

IFR (2018). *Robot density rises globally.* URL: https://ifr.org/news/robot-density-rises-globally/ (visited on 11/10/2021).

Jacobson, Louis S., Robert J. Lalonde, and Daniel G. Sullivan (1993). “Earnings Losses of Displaced Workers”. *American Economic Review* 83.4, pp. 685–709. URL: https://www.jstor.org/stable/2117574.

Klenert, David, Enrique Fernández Macías, and José Ignacio Antón Pérez (2020). “Do robots really destroy jobs? Evidence from Europe”.

Kline, Patrick and Enrico Moretti (2014). “People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs”. *Annual Review of Economics* 6.14, pp. 629–662. DOI: 10.1146/annurev-economics-080213-041024.

Koch, Michael, Ilya Manuylov, and Marcel Smolka (2021). “Robots and Firms”. *Economic Journal* 131.638, pp. 2553–2584. DOI: 10.1093/ej/ueab009.

Korchowiec, Bartosz (2019). “Job Automation and Worker Reallocation”. *Job Market Paper*.

Kurer, Thomas (2020). “The Declining Middle: Occupational Change, Social Status, and the Populist Right”. *Comparative Political Studies* 53.10-11, pp. 1798–1835. DOI: 10.1177/0010414020912283.

Kurer, Thomas and Aina Gallego (2019). “Distributional consequences of technological change: Worker-level evidence”. *Research and Politics* 6.1. DOI: 10.1177/2053168018822142.

Lalive, Rafael (2007). “Unemployment benefits, unemployment duration, and post-unemployment jobs: A regression discontinuity approach”. *American Economic Review* 97.2, pp. 108–112. DOI: 10.1257/aer.97.2.108.

Lee, Donghoon and Kenneth I. Wolpin (2006). “Intersectoral labor mobility and the growth of the service sector”. *Econometrica* 74.1, pp. 1–46. DOI: 10.1111/j.1468-0262.2006.00648.x.

Lee, Neil, Katy Morris, and Thomas Kemeny (2018). “Immobility and the Brexit vote”. *Cambridge Journal of Regions, Economy and Society* 11, pp. 143–163. DOI: 10.1093/cjres/rsx027.

Leigh, Nancey Green, Benjamin Kraft, and Heonyeong Lee (2020). “Robots, skill demand and manufacturing in US regional labour markets”. *Cambridge Journal of Regions, Economy and Society* 13.1, pp. 77–97. DOI: 10.1093/cjres/rsz019.

Leigh, Nancey Green and Benjamin R. Kraft (2018). “Emerging robotic regions in the United States: insights for regional economic evolution”. *Regional Studies* 52.6, pp. 804–815. DOI: 10.1080/00343404.2016.1269158.

Los, Bart, Philip McCann, John Springford, and Mark Thissen (2017). “The mismatch between local voting and the local economic consequences of Brexit”. *Regional Studies* 51.5, pp. 786–799. DOI: 10.1080/00343404.2017.1287350.

Mann, Katja and Lukas Püttmann (2021). “Benign Effects of Automation: New Evidence from Patent Texts”. *Review of Economics and Statistics.* DOI: 10.1162/rest_a_01083.

Mayor, Matías, Begoña Cueto, and Patricia Suárez (2015). “Fostering the Self-Employment in Spain: An Evaluation of the Capitalisation of Unemployment Benefits Programme”. In: *Geographical labor market imbalances.* Ed. by Chiara Mussida and Francesco Pastore. Springer, pp. 335–352. DOI: 10.1007/978-3-642-55203-8_15.

McCann, Philip (2018). “The trade, geography and regional implications of Brexit”. *Papers in Regional Science* 97.1, pp. 3–8. DOI: 10.1111/pirs.12352.

Melguizo, Celia and Vicente Royuela (2020). “What drives migration moves to urban areas in Spain? Evidence from the Great Recession”. *Regional Studies* 54.12, pp. 1680–1693. DOI: 10.1080/00343404.2020.1747606.

Milner, Helen V. (2021). “Voting for Populism in Europe: Globalization, Technological Change, and the Extreme Right”. *Comparative Political Studies* 54.13, pp. 2286–2320. DOI: 10.1177/0010414021997175.

Mitchell, Tom and Erik Brynjolfsson (2017). “Track how technology is transforming work”. *Nature* 544.7650, pp. 290–292. DOI: 10.1038/544290a.

Moll, Benjamin, Lukasz Rachel, and Pascual Restrepo (2021). “Uneven Growth: Automation’s Impact on Income and Wealth Inequality”. *NBER Working Paper 28440.* DOI: 10.2139/ssrn.3801089.

Moretti, Enrico (2012). *The New Geography of Jobs.* New York: Houghton Mifflin Harcourt. ISBN: 978-0-547-75011-8.

Nakamura, Hideki and Joseph Zeira (2018). “Automation and Unemployment: Help Is on the Way”. DOI: 10.2139/ssrn.3202622.

Nienhüser, Werner and Wenzel Matiaske (2006). “Effects of the ’principle of non-discrimination’ on temporary agency work: compensation and working conditions of temporary agency workers in 15 European countries”. *Industrial Relations Journal* 37.1, pp. 64–77. DOI: 10.1111/j.1468-2338.2006.00390.x.

Noelke, Clemens and Mauricio Avendano (2015). “Who Suffers during Recessions? Economic Downturns, Job Loss, and Cardiovascular Disease in Older Americans”. *American Journal of Epidemiology* 182.10, pp. 873–882. DOI: 10.1093/aje/kwv094.

OECD (2021). *Temporary employment (indicator).* DOI: 10.1787/75589b8a-en. (Visited on 11/11/2021).

Olea, José Luis Montiel and Carolin Pflueger (2013). “A Robust Test for Weak Instruments”. *Journal of Business and Economic Statistics* 31.3, pp. 358–369. DOI: 10.1080/00401706.2013.806694.

Petrova, Maria, Gregor Schubert, Pinar Yildirimi, and Bledi Taska (2021). "Automation, Career Values, and Political Preferences". *Working Paper*.

Pratt, Gill A. (2015). "Is a Cambrian Explosion coming for robotics?" *Journal of Economic Perspectives* 29.3, pp. 51–60. DOI: 10.1257/jep.29.3.51.

Raj, Manav and Robert Seamans (2019). "Artificial Intelligence, Labor, Productivity, and the Need for Firm- Level Data". In: *The Economics of Artificial Intelligence: An Agenda Volume*. Ed. by Ajay Agrawal, Joshua Gans, and Avi Goldfarb. University of Chicago Press. Chap. 22, pp. 553–565. ISBN: 978-0-226-61347-5.

Riumallo-Herl, Carlos, Sanjay Basu, David Stuckler, Emilie Courtin, and Mauricio Avendano (2014). "Job loss, wealth and depression during the Great Recession in the USA and Europe". *International Journal of Epidemiology* 43.5, pp. 1508–1517. DOI: 10.1093/ije/dyu048.

Rodríguez-Pose, Andrés (2018). "The revenge of the places that don't matter (and what to do about it)". *Cambridge Journal of Regions, Economy and Society* 11, pp. 189–209. DOI: 10.1093/cjres/rsx024.

Ruhm, Christopher J. (1991). "Are Workers Permanently Scarred by Job Displacements?" *American Economic Review* 81.1, pp. 319–324. URL: https://www.jstor.org/stable/2006805.

Seguridad Social (2021). *MCVL. Muestra continua de vidas laborales. Guía del contenido.* Tech. rep. URL: https://www.seg-social.es/wps/portal/wss/internet/EstadisticasPresupuestosEstudios/Estadisticas/EST211/1429.

Stevens, Ann Huff (1997). "Persistent Effects of Job Displacement : The Importance of Multiple Job Losses". *Journal of Labor Economics* 15.1, pp. 165–188. DOI: 10.1086/209851.

Sullivan, Daniel G. and Till von Wachter (2009). "Job Displacement and Mortality: An Analysis Using Administrative Data". *Quarterly Journal of Economics* 124.3, pp. 1265–1306. DOI: 10.1162/qjec.2009.124.3.1265.

Van Reenen, John (2011). "Wage inequality, technology and trade: 21st century evidence". *Labour Economics* 18.6, pp. 730–741. DOI: 10.1016/j.labeco.2011.05.006.

Tables

Table 1: IFR categories and aggregation schemes

Code	Name	15 Groups	17 Groups	19 Groups	20 Groups
A-B	Agriculture, forestry, fishing	01–03	01–03	01–03	01–03
C	Mining and quarrying	05–09	05–09	05–09	05–09
D	Manufacturing				
10–12	Food and beverages	10–12	10–12	10–12	10–12
13–15	Textiles	13–15	13–15	13–15	13–15
16	Wood and furniture	16,31	16,31	16,31	16,31
17–18	Paper	17–18	17–18	17–18	17–18
19–22	Plastic and chemical products	19–22	19–22		
19	Pharmaceuticals, cosmetics	19–22	19–22	19–21	19
20–21	other chemical products n.e.c.	19–22	19–22	19–21	20–21
22	Rubber and plastic products (non-automotive)	19–22	19–22	22	22
229	Chemical products, unspecified				
23	Non-metallic mineral products	23	23	23	23
24–28	Metal	24,25,28			
24	Basic metals	24,25,28	24	24	24
25	Metal products (non-automotive)	24,25,28	25	25	25
28	Industrial machinery	24,25,28	28	28	28
289	Metal, unspecified				
26–27	Electrical/electronics	26–27	26–27		
275	Household/domestic appliances			27	27
271	Electrical machinery n.e.c. (non-automotive)			27	27
260	Electronic components/devices			26	26
261	Semiconductors, LCD, LED			26	26
262	Computers and peripheral equipment			26	26
263	Communication equipment			26	26
265	Medical, precision, optical instruments			26	26
279	Electrical/electronics unspecified				
29	Automotive	29	29	29	29
291	Motor vehicles, engines and bodies				
293	Automotive parts				
2931	Metal (AutoParts)				
2932	Rubber and plastic (AutoParts)				
2933	Electrical/electronic (AutoParts)				
2934	Glass (AutoParts)				
2939	Other (AutoParts)				
2999	Unspecified AutoParts				
299	Automotive unspecified				
30	Other vehicles	30	30	30	30
91*	All other manufacturing branches				
E	Electricity, gas, water supply	35–39	35–39	35–39	35–39
F	Construction	41–43	41–43	41–43	41–43
P	Education/research/development	72,85	72,85	72,85	72,85
90*	All other non-manufacturing branches				
99*	Unspecified				

Notes: "*" indicates residual categories whose robots are excluded from all aggregation schemes.

Table 2: Summary statistics, transition level

Qualitative	MLS		HS		Total	
	%	Corr.	%	Corr.	%	Corr.
Worse pay	41.39		41.47		41.41	
Worse security	8.32	-0.002	11.50	0.075	9.03	0.017
Lower skill	10.94	0.069	36.91	0.179	16.71	0.097
Employed in ETT firm	5.00	0.012	2.58	0.025	4.46	0.014
Female	36.26	-0.014	54.54	0.017	40.32	-0.007
Change sector	47.85	0.058	43.28	0.101	46.83	0.067
Change NUTS3	15.42	0.018	21.98	0.002	16.87	0.014
Temporary contract (prev.)	83.70	0.042	60.86	0.074	78.62	0.049
Manufacturing (prev.)	11.79	0.023	5.47	-0.003	10.39	0.018
Birth Place						
Spain	80.58	-0.009	91.24	-0.009	82.95	-0.009
Center and South America	8.12	0.008	3.95	0.007	7.19	0.008
EU28	4.72	-0.001	3.08	0.005	4.36	0.000
Africa	4.58	0.005	0.73	0.001	3.73	0.005
Other	2.00	0.004	1.00	0.002	1.78	0.004
Year of start						
2001 - 2003	17.76	-0.005	14.61	-0.038	17.06	-0.012
2004 - 2006	25.43	-0.033	21.90	-0.057	24.65	-0.038
2007 - 2009	23.73	-0.005	23.47	-0.025	23.67	-0.009
2010 - 2012	18.46	0.032	21.95	0.062	19.24	0.039
2013 - 2015	9.33	0.021	12.05	0.054	9.93	0.029
2016 - 2018	5.29	-0.001	6.02	0.018	5.45	0.003
Quantitative	MLS		HS		Total	
	Mean	Corr.	Mean	Corr.	Mean	Corr.
Pay ratio	111.065	-0.636	108.039	-0.625	110.393	-0.633
Δ robots	0.077	0.025	0.027	-0.008	0.066	0.020
Δ imports from China	0.076	0.004	0.038	-0.001	0.068	0.003
Δ ICT stock	0.387	-0.002	0.563	-0.001	0.426	-0.002
Age	34.571	-0.010	35.467	-0.032	34.770	-0.014
Weeks unemployed	33.470	-0.027	29.158	0.054	32.512	-0.010
Unobs. ability	-0.003	0.024	0.108	0.005	0.022	0.020
N	1,035,553		295,687		1,331,240	

Notes: Summary statistics on the estimation sample. Statistics on the 1-digit sector and NUTS2 area of the previous occupation are not included in this table but can be found in Figure 2 and 3, respectively. Columns "Corr." report the correlation between each variable and the dummy for "Worse pay". *Sources*: MCVL, IFR, INE, EU-KLEMS and Eurostat, own calculations.

Table 3: Results - Heterogeneity - Lower pay and pay ratio

	HS			MLS		
	Group 1	Group 2	Diff	Group 1	Group 2	Diff
Lower Pay						
Gender						
ΔExp	0.006	-0.003	0.009	0.029 $***$	0.018 $***$	0.011 $***$
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.023 $**$	-0.018 $***$	-0.005	0.015 $***$	0.003	0.011 $***$
$\Delta Exp \cdot (\Delta Sector = 1)$	0.029 $***$	0.024 $***$	0.005	0.038 $***$	0.032 $***$	0.006
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.009	-0.001	0.011	0.028 $***$	0.018 $***$	0.010 $***$
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.020	-0.015	-0.004	0.041 $***$	0.027 $***$	0.014 $*$
N	161,265	134,422		375,506	660,047	
Age						
ΔExp	-0.004	0.003	-0.006	0.016 $***$	0.022 $***$	-0.006
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.017 $***$	-0.018 $***$	0.001	0.004	0.006 $***$	-0.002
$\Delta Exp \cdot (\Delta Sector = 1)$	0.023 $***$	0.028 $***$	-0.005	0.031 $***$	0.034 $***$	-0.003
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.003	0.007	-0.010	0.016 $***$	0.021 $***$	-0.005
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.010	-0.019	0.008	0.020 $***$	0.033 $***$	-0.012
N	86,555	209,132		300,687	734,866	
Urbanisation						
ΔExp	0.003	-0.004	0.007	0.021 $***$	0.022 $***$	-0.001
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.018 $***$	-0.018 $***$	0.001	0.006 $**$	0.005 $**$	0.000
$\Delta Exp \cdot (\Delta Sector = 1)$	0.031 $***$	0.020 $**$	0.011	0.031 $***$	0.035 $***$	-0.004
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.004	0.000	0.004	0.019 $***$	0.021 $***$	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.009	-0.018	0.008	0.034 $***$	0.029 $***$	0.005
N	123,098	172,589		327,296	708,257	
Empl. in Manufacturing						
ΔExp	0.007	-0.007	0.014 $*$	0.021 $***$	0.020 $***$	0.001
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.009 $*$	-0.026 $***$	0.017 $**$	0.008 $***$	0.002	0.006
$\Delta Exp \cdot (\Delta Sector = 1)$	0.030 $***$	0.023 $***$	0.007	0.031 $***$	0.035 $***$	-0.004
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.008	-0.004	0.012	0.020 $***$	0.019 $***$	0.001
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.004	-0.019	0.015	0.031 $***$	0.027 $***$	0.004
N	71,239	224,448		235,322	800,231	
Pay Ratio						
Gender						
ΔExp	-0.609	-0.376 $*$	-0.233	-2.646 $***$	-1.666 $***$	-0.980 $***$
$\Delta Exp \cdot (\Delta Sector = 0)$	0.902	0.343 $*$	0.560	-0.990 $***$	-0.244 $*$	-0.746 $***$
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.817 $**$	-1.742 $***$	-0.075	-3.585 $***$	-2.880 $***$	-0.705 $*$
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.690	-0.537 $**$	-0.153	-2.525 $***$	-1.543 $***$	-0.982 $***$
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.053	0.483	-0.536	-3.904 $***$	-2.744 $***$	-1.160
N	161,265	134,422		375,506	660,047	
Age						
ΔExp	-0.248	-0.649 $**$	0.401	-1.445 $***$	-2.038 $***$	0.592 $**$
$\Delta Exp \cdot (\Delta Sector = 0)$	0.508 $**$	0.303	0.206	-0.274	-0.483 $***$	0.209
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.806 $***$	-1.794 $***$	-0.013	-2.850 $***$	-3.124 $***$	0.275
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.365	-0.829 $***$	0.464	-1.278 $***$	-1.922 $***$	0.644 $**$
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.515	0.284	0.231	-3.392 $***$	-3.052 $***$	-0.340
N	86,555	209,132		300,687	734,866	
Urbanisation						
ΔExp	-0.659 $**$	-0.250	-0.409	-1.899 $***$	-1.911 $***$	0.012
$\Delta Exp \cdot (\Delta Sector = 0)$	0.231	0.636 $*$	-0.404	-0.650 $***$	-0.261	-0.389
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.885 $***$	-1.703 $***$	-0.183	-2.777 $***$	-3.289 $***$	0.512
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.688 $**$	-0.499	-0.189	-1.825 $***$	-1.728 $***$	-0.097
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.388	0.652	-1.041	-2.828 $***$	-3.217 $***$	0.389
N	123,098	172,589		327,296	708,257	
Empl. in Manufacturing						
ΔExp	-0.728 $***$	-0.240	-0.488	-1.909 $***$	-1.826 $***$	-0.083
$\Delta Exp \cdot (\Delta Sector = 0)$	0.190	0.613 $**$	-0.423	-0.619 $***$	-0.212	-0.407
$\Delta Exp \cdot (\Delta Sector = 1)$	-2.011 $***$	-1.588 $***$	-0.423	-2.857 $***$	-3.139 $***$	0.282
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.806 $***$	-0.418	-0.387	-1.837 $***$	-1.661 $***$	-0.175
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.201	0.395	-0.194	-2.694 $***$	-3.071 $***$	0.377
N	71,239	224,448		235,322	800,231	

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. All regressions include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal. Group 1 and Group 2 are defined as follows. Gender: (1) Female, (2) Male. Age: (1) $\geq$ 40, (2) $<$ 40. Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no. *Sources*: MCVL, IFR, INE, EU-KLEMS, UN-Comtrade and Eurostat, own calculations.

Table 4: Results - Heterogeneity - Lower skill and less security

	HS			MLS		
	Group 1	Group 2	Diff	Group 1	Group 2	Diff
Lower skill						
Gender						
ΔExp	0.017 **	0.005	0.012	0.012 ***	0.009 ***	0.003
$\Delta Exp \cdot (\Delta Sector = 0)$	0.010	0.005	0.005	0.010 ***	0.003 **	0.007 **
$\Delta Exp \cdot (\Delta Sector = 1)$	0.022 **	0.006	0.016	0.014 ***	0.015 ***	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.019 **	0.004	0.015	0.013 ***	0.010 ***	0.003
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.002	0.011	-0.009	0.004	0.004 *	-0.000
N	161,265	134,422		375,506	660,047	
Age						
ΔExp	0.003	0.013 **	-0.010	0.003 *	0.012 ***	-0.009 ***
$\Delta Exp \cdot (\Delta Sector = 0)$	0.003	0.008	-0.005	0.001	0.005 ***	-0.004 *
$\Delta Exp \cdot (\Delta Sector = 1)$	0.001	0.018 **	-0.018	0.005 *	0.016 ***	-0.011 ***
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.000	0.015 **	-0.015 *	0.003 *	0.012 ***	-0.009 ***
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.020	0.004	0.016	0.002	0.004 *	-0.003
N	86,555	209,132		300,687	734,866	
Urbanisation						
ΔExp	0.006	0.012 **	-0.005	0.011 ***	0.008 ***	0.003
$\Delta Exp \cdot (\Delta Sector = 0)$	0.001	0.013 *	-0.012	0.002	0.006 ***	-0.004 *
$\Delta Exp \cdot (\Delta Sector = 1)$	0.014	0.010	0.004	0.018 ***	0.011 ***	0.008 **
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.007	0.011 *	-0.004	0.012 ***	0.009 ***	0.003
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.001	0.016	-0.015	0.005	0.003	0.002
N	123,098	172,589		327,296	708,257	
Empl. in Manufacturing						
ΔExp	0.005	0.012 *	-0.007	0.012 ***	0.007 ***	0.005 **
$\Delta Exp \cdot (\Delta Sector = 0)$	0.001	0.011	-0.011	0.003 *	0.003 **	0.000
$\Delta Exp \cdot (\Delta Sector = 1)$	0.010	0.013	-0.002	0.018 ***	0.010 ***	0.008 **
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.004	0.013	-0.009	0.012 ***	0.008 ***	0.004 *
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.016	0.010	0.005	0.008 ***	0.000	0.008 *
N	71,239	224,448		235,322	800,231	
Worse sec						
Gender						
ΔExp	-0.001	-0.000	-0.001	-0.009 *	-0.010 ***	0.001
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.000	-0.005 *	0.005	-0.024 ***	-0.019 ***	-0.005
$\Delta Exp \cdot (\Delta Sector = 1)$	-0.001	0.012	-0.013	0.006	0.011 *	-0.005
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.002	-0.000	0.002	-0.012 **	-0.010 ***	-0.002
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.024	0.001	-0.025	0.022 **	-0.001	0.023 **
N	43,523	52,890		74,625	88,768	
Age						
ΔExp	-0.003	0.004	-0.007	-0.012 ***	-0.008 **	-0.004
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.005	-0.004	-0.001	-0.024 ***	-0.018 ***	-0.007
$\Delta Exp \cdot (\Delta Sector = 1)$	-0.000	0.018 *	-0.019	0.015 *	0.008	0.007
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.001	0.002	-0.004	-0.012 ***	-0.010 ***	-0.002
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.018 *	0.015	-0.034 *	-0.010	0.013 **	-0.023 **
N	39,858	56,555		65,960	97,433	
Urbanisation						
ΔExp	0.003	-0.004	0.007	-0.015 ***	-0.003	-0.012 **
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.003	-0.004	0.002	-0.022 ***	-0.018 ***	-0.005
$\Delta Exp \cdot (\Delta Sector = 1)$	0.014	-0.002	0.015	-0.002	0.026 ***	-0.029 ***
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.004	-0.004	0.007	-0.016 ***	-0.004	-0.011 *
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.002	-0.004	0.002	-0.002	0.011	-0.013
N	49,900	46,513		63,696	99,697	
Empl. in Manufacturing						
ΔExp	-0.003	0.003	-0.006	-0.014 ***	-0.006	-0.008
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.005	-0.002	-0.004	-0.021 ***	-0.019 ***	-0.002
$\Delta Exp \cdot (\Delta Sector = 1)$	0.001	0.013	-0.012	-0.001	0.024 ***	-0.025 **
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.003	0.004	-0.007	-0.015 ***	-0.006	-0.008
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.003	-0.002	-0.001	0.003	0.006	-0.003
N	25,985	70,428		44,270	119,123	

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. All regressions include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal. Group 1 and Group 2 are defined as follows. Gender: (1) Female, (2) Male. Age: (1) $\geq$ 40, (2) $<$ 40. Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no. *Sources*: MCVL, IFR, INE, EU-KLEMS, UN-Comtrade and Eurostat, own calculations.

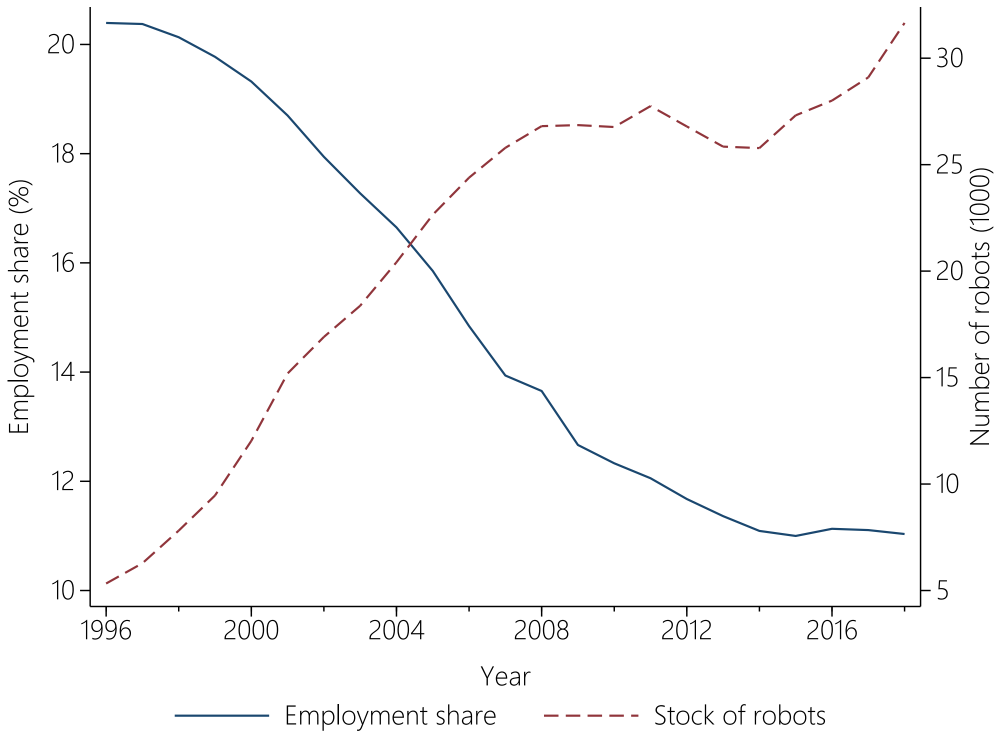
Table 5: Results - Heterogeneity - In ETT firm

	HS			MLS		
	Group 1	Group 2	Diff	Group 1	Group 2	Diff
Gender						
ΔExp	0.005	0.001	0.004	0.016 $***$	0.011 $***$	0.005 $*$
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.009 $**$	0.002	0.007	0.016 $***$	0.012 $***$	0.004
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.019 $**$	-0.002	-0.017 $**$	0.014 $***$	0.000	0.014 $**$
N	71,239	224,448		235,322	800,231	
Age						
ΔExp	0.001	0.004	-0.003	0.010 $***$	0.012 $***$	-0.002
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.001	0.006 $**$	-0.006	0.010 $***$	0.013 $***$	-0.003
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.002	-0.011 $**$	0.013 $*$	0.012 $*$	0.001	0.012
N	71,239	224,448		235,322	800,231	
Urbanisation						
ΔExp	0.005 $*$	-0.001	0.007 $*$	0.011 $***$	0.011 $***$	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.006 $*$	0.000	0.006	0.011 $***$	0.013 $***$	-0.002
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.004	-0.006	0.002	0.003	0.002	0.001
N	71,239	224,448		235,322	800,231	
Empl. in Manufacturing						
ΔExp	0.003	0.001	0.002	0.010 $***$	0.011 $***$	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.004	0.003	0.001	0.011 $***$	0.011 $***$	-0.000
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.005	-0.005	-0.000	-0.005 $**$	0.009 $**$	-0.014 $***$
N	71,239	224,448		235,322	800,231	

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. All regressions include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal. Group 1 and Group 2 are defined as follows. Gender: (1) Female, (2) Male. Age: (1) ≥ 40, (2) < 40. Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no. *Sources*: MCVL, IFR, INE, EU-KLEMS, UN-Comtrade and Eurostat, own calculations.

Figures

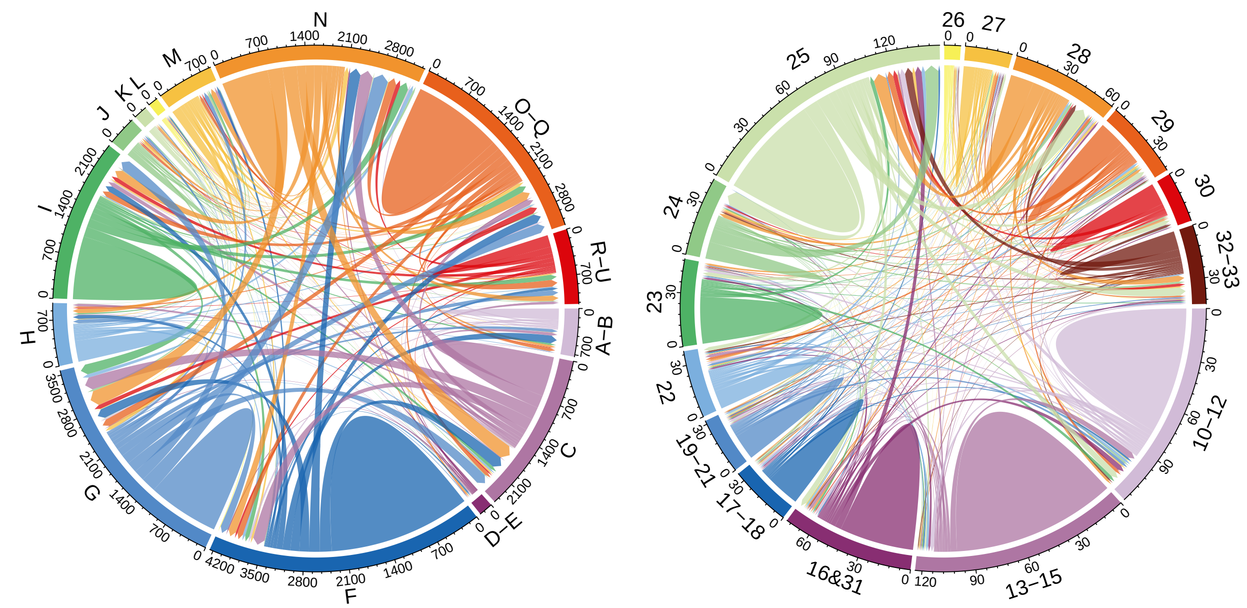
Figure 1: Manufacturing employment share and stock of robots



Sources: INE and IFR, own calculations.

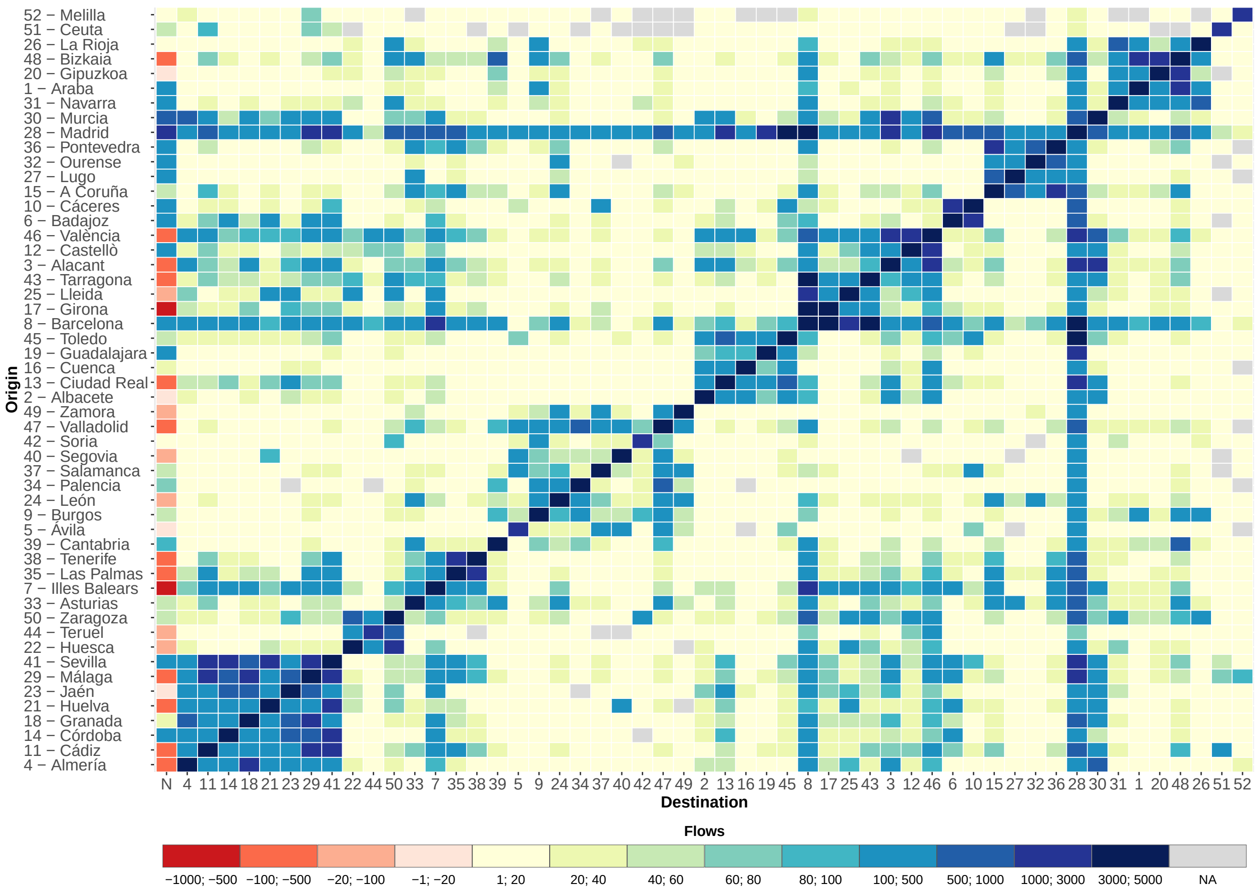
Figure 2: Flows by sector (NACE Rev.2 codes)

(a) Across 1-digit sectors (b) Within manufacturing



Notes: summary statistics on the estimation sample. Flows are reported in hundreds of transitions. 1-digit sectors: "A-B - Agriculture and mining", "C - Manufacturing", "D-E - Energy, water and waste", "F - Construction", "G - Wholesale and retail trade; repair of motor vehicles", "H - Transporting and storage", "I - Accommodation and food", "J - Information and communication", "K - Finance and insurance", "L - Real estate", "M - Professional, scientific and technical activities", "N - Administrative and support services", "O-Q - Public administration and defence, compulsory social security, education and social work", "R-U - Arts, entertainment and other services". 2-digit manufacturing sectors: "10-12 - Food and beverages", "13-15 - Textiles", "16&31 - Wood and Furniture", "17-18 - Paper", "19-21 - Refined petroleum, chemical and pharmaceutical products", "22 - Rubber", "23 - Non-metallic mineral products", "24 - Basic metals", "25 - Metal products", "26 - Computer, electronic and optical products", "27 - Electrical equipment", "28 - machinery and equipment n.e.c.", "29 - Motor vehicles, trailers and semi-trailers", "30 - Other transport equipment", "32-33 - Other manufacturing, repair and installation". *Source:* MCVL, own calculations.

Figure 3: Flows by province

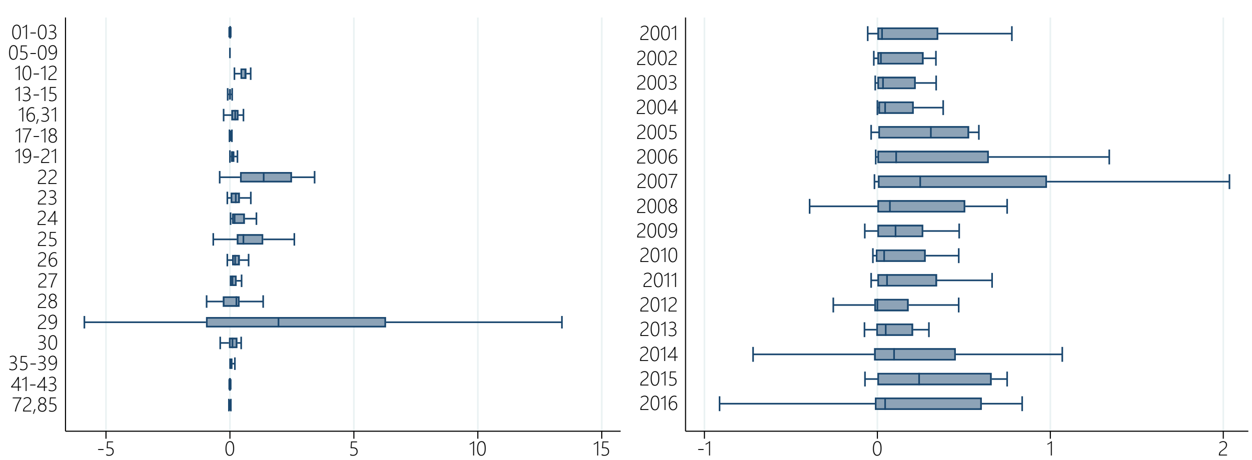


Notes: summary statistics on the estimation sample. For each row, column "N" reports the net inflows by province, while columns 1-52 report bilateral flows. *Source:* MCVL, own calculations.

Figure 4: Variation in robot adoption in Spain

(a) Variation by sector

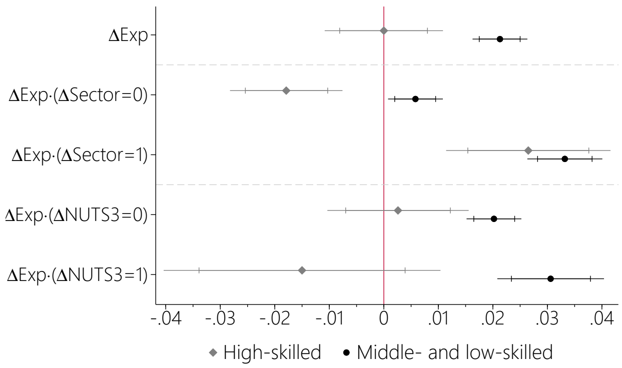
(b) Variation by year



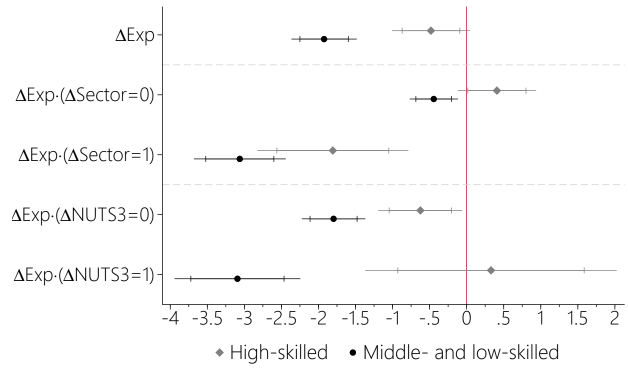
Source: IFR, own calculations.

Figure 5: Effect of exposure to industrial robots on pay, employment security and qualification

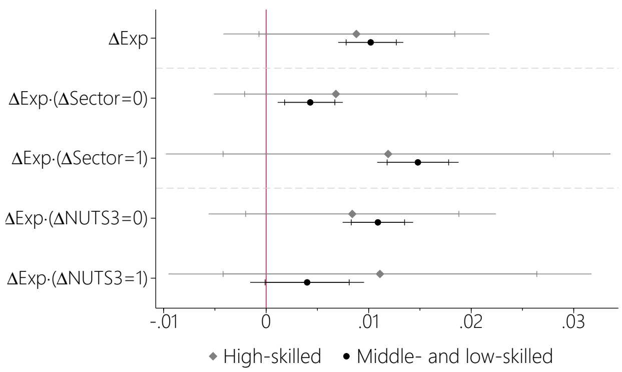
(a) Probability of lower pay



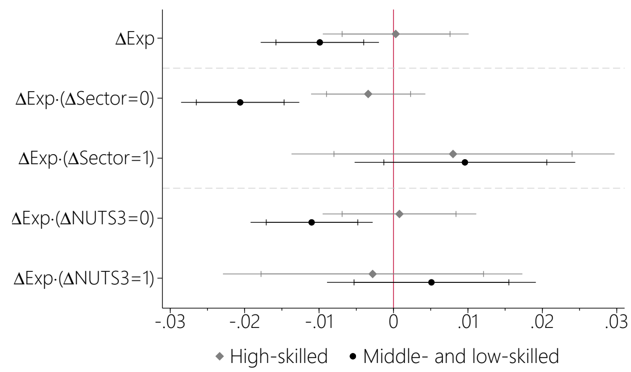
(b) Ratio of new pay over previous pay (x100)



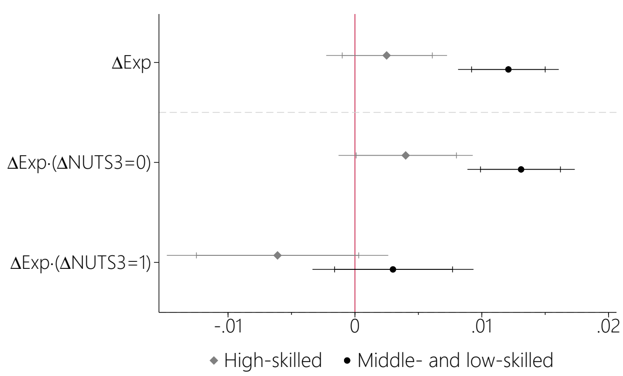
(c) Probability of lower qualification requirement



(d) Probability of temporary contract



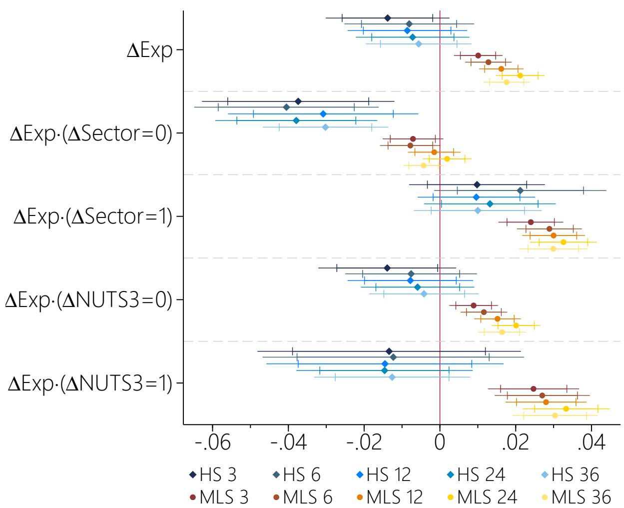
(e) Probability of being in ETT



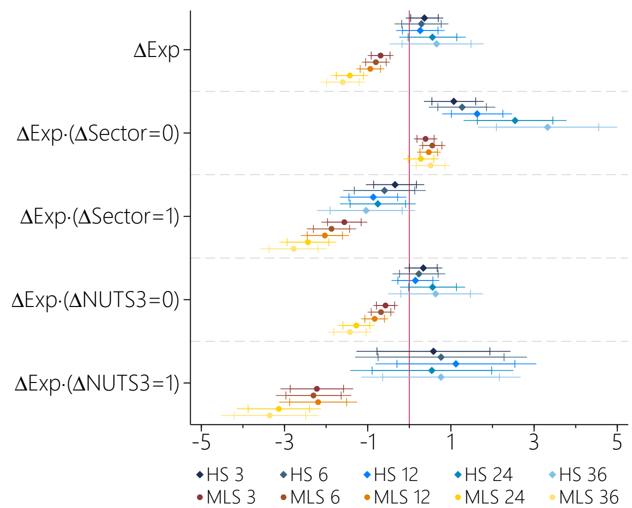
Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal. Confidence intervals are reported both at the 95% (vertical bars) and 99% (horizontal lines) level. The sample size is 1,035,553 for middle- and low-skilled and 295,687 for high-skilled in Panel 5a, 5b and 5c. Panel 5d focuses on transitions from jobs with a permanent contract, hence the sample size is 163,393 for middle- and low-skilled and 96,413 for high-skilled. Also Panel 5e has a reduced sample: 966,016 for MLS and 292,476 for HS. Olea and Pflueger (2013) first-stage F-Stat is 203.6 (165.1) for middle- and low-skilled (high-skilled) in Panel 5a, 5b and 5c and 111.42 (127.1) in Panel 5d. *Sources*: MCVL, IFR, INE, EU-KLEMS, UN-Comtrade and Eurostat, own calculations.

Figure 6: Results - Medium term

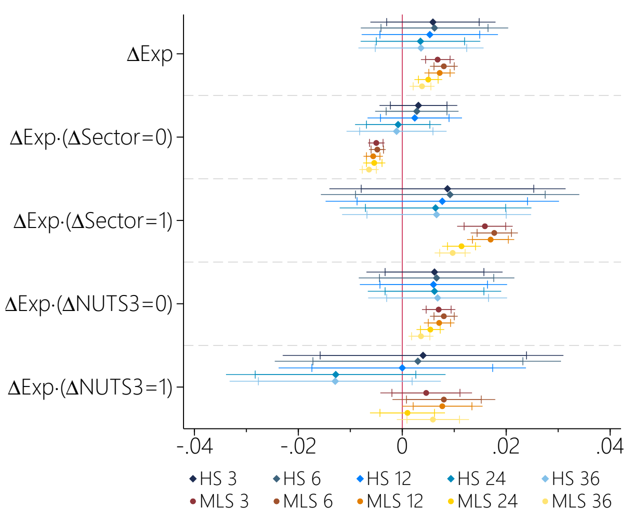
(a) Probability of lower pay



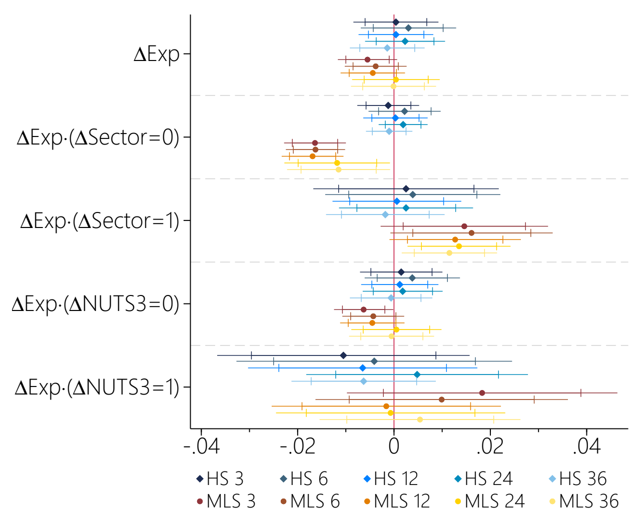
(b) Ratio of new pay over previous pay (x100)



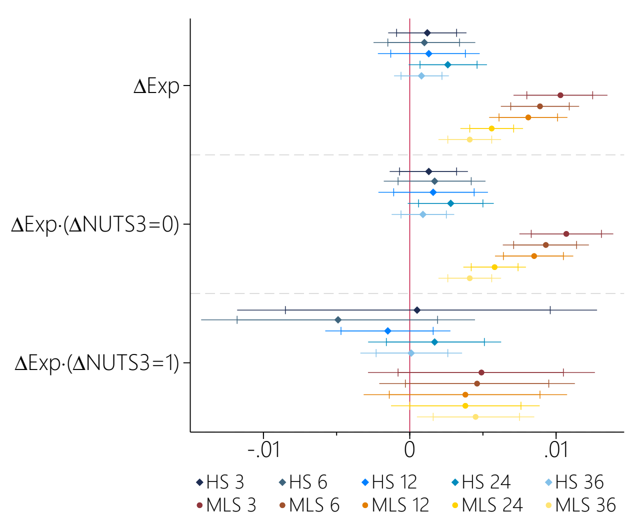
(c) Probability of lower qualification requirement



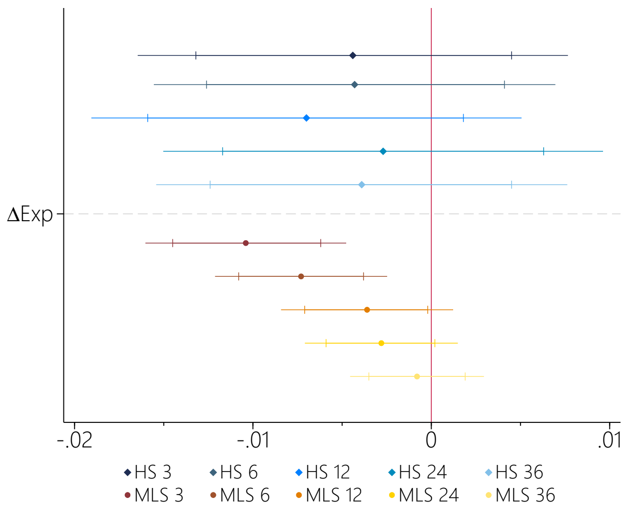
(d) Probability of temporary contract



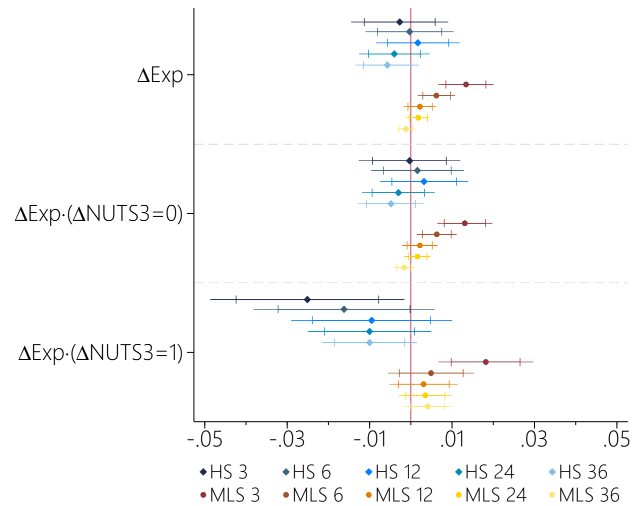
(e) Probability of being in ETT



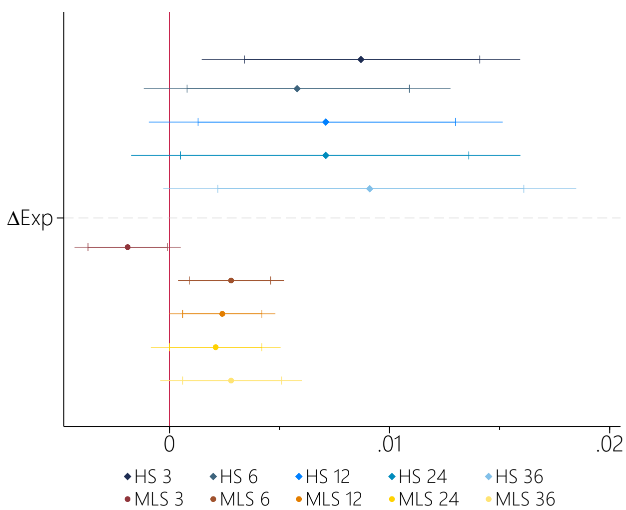
(f) Probability of being working



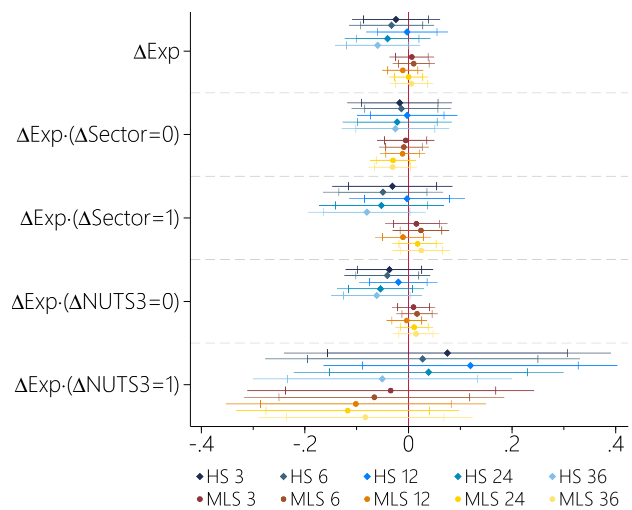
(g) Probability of being unemployed (with benefits)



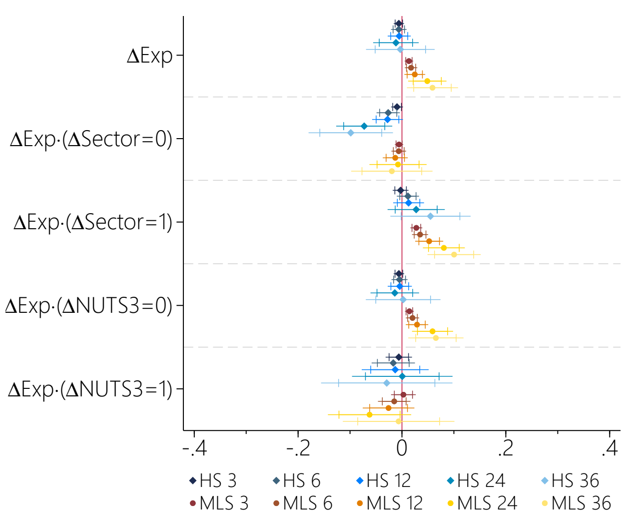
(h) Probability of being out of Seg.Soc.



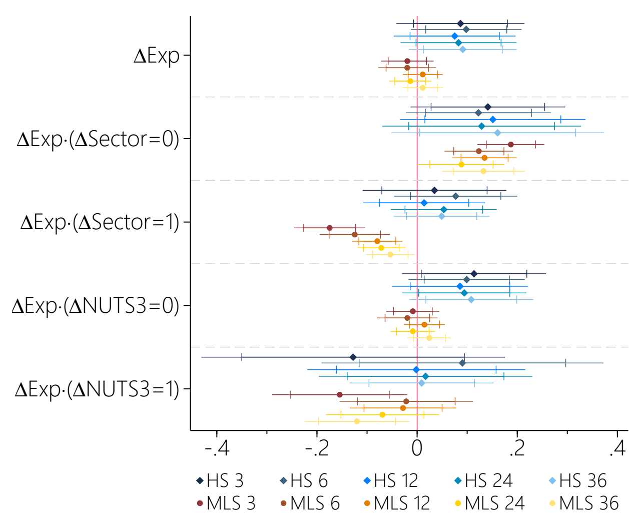
(i) Number of different employers

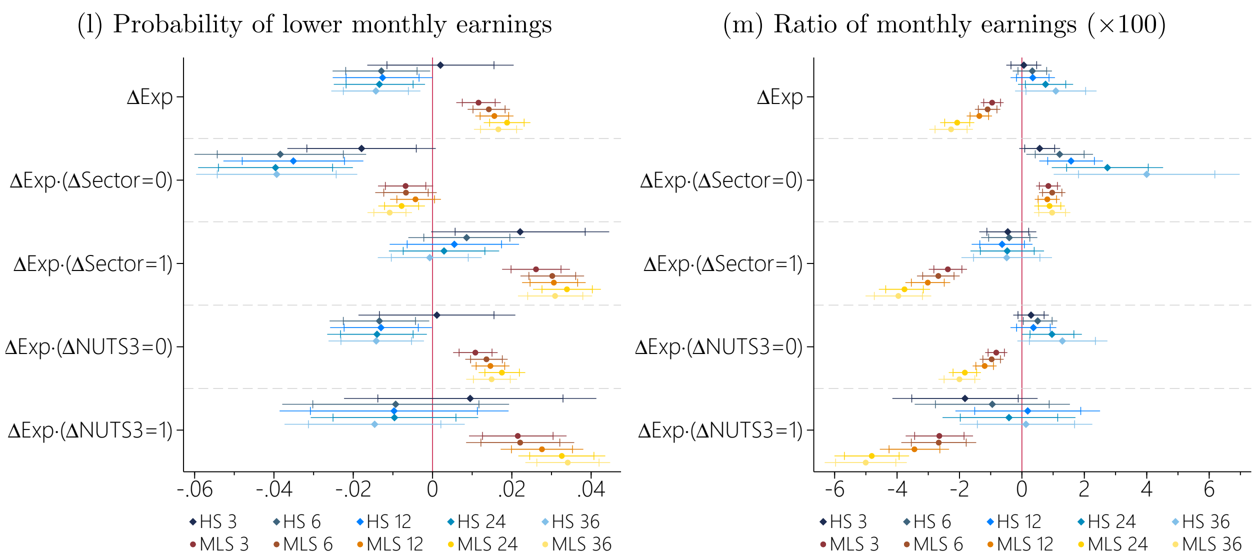


(j) Number of contracts



(k) Number of effective days worked in month



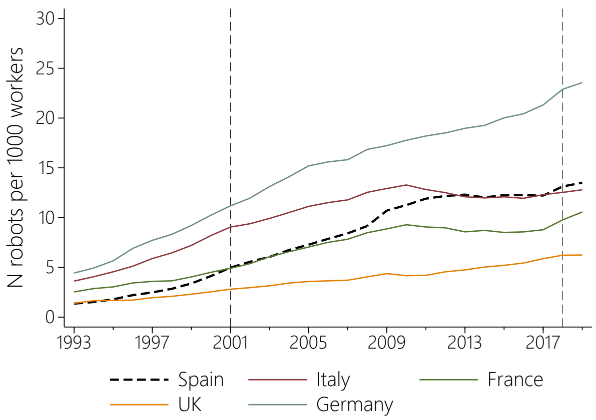


Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal. Confidence intervals are reported both at the 95% (vertical bars) and 99% (horizontal lines) level.
Sources: MCVL, IFR, INE, EU-KLEMS, UN-Comtrade and Eurostat, own calculations.

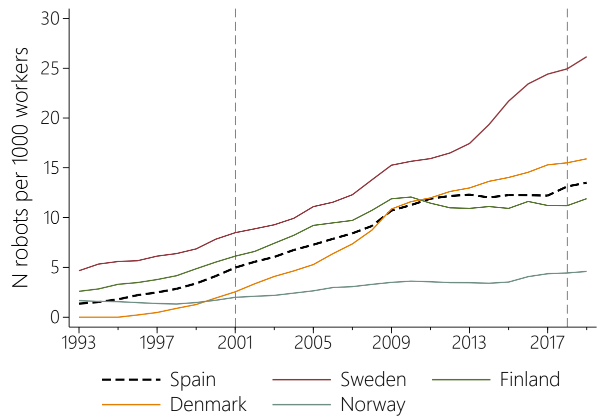
A Appendix - Additional content

Figure A1: Robot density in manufacturing - Spain and possible instruments

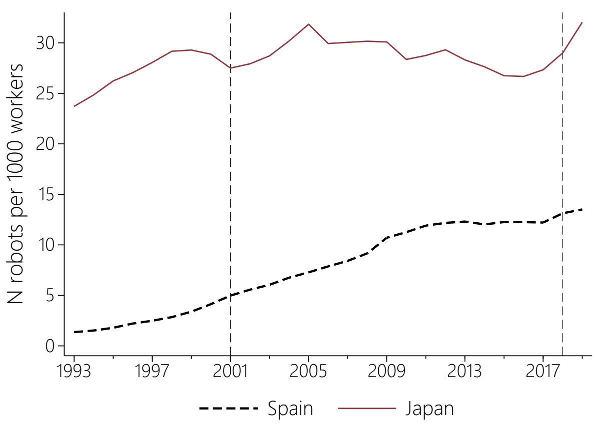
(a) Southern and Western Countries



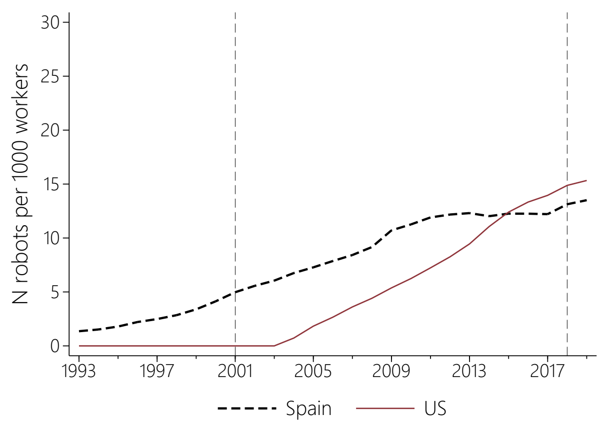
(b) Nordic Countries



(c) Japan



(d) US



Sources: IFR and ILO, own calculations.

Table A1: Year of start of robot data by Country and sector

Sector	ES	IT	FR	DE	UK	SE	DK	FI	NO	US	JP
01–03	2004	2005	2005	1998	1995	2004	2002	2000	2000	2007	1995
05–09	2004	2000	2006	2008	1998	2010	1999	2008	2015	2007	1996
10–12	1995	1995	1995	1995	1995	1995	1996	1995	1995	2004	1995
13–15	1995	1995	1995	1995	1995	1995	1996	1995	2002	2007	1995
16,31	1995	1995	1995	1995	1995	1995	1997	1995	1995	2006	1995
17–18	1995	1995	1995	1995	1997	1995	2004	1995	1995	2007	1995
19–21	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004	2010
22	2004	2004	2004	2004	2004	2004	2004	2004	2005	2004	2010
23	1995	1995	1995	1995	1995	1995	2005	1995	1995	2006	1995
24	1995	1995	1995	1995	1995	1995	1996	1995	1995	2008	1995
25	1995	1995	1995	1995	1995	1995	1996	1995	1995	2004	1995
26	1996	1995	2005	1995	1996	1995	1998	1995	1995	2007	1995
27	2005	2005	2004	2004	2004	2004	2004	2004	2004	2007	2010
28	1995	1995	1995	1995	1995	1995	1996	1995	1995	2007	1995
29	1995	1995	1995	1995	1995	1995	1996	1995	1995	2004	1995
30	1995	1995	1995	1996	1995	1995	2005	1995	1995	2006	1995
35–39	2002	2000	2005	1998	1997	1997	2013	2015	2000	2011	1996
41–43	1995	2000	2005	1997	1996	1996	2004	1997	2014	2006	1996
72,85	1995	1996	2005	1996	1996	1995	1998	1996	1996	2005	1996

Notes: in our baseline specification we consider displacements occurring between 2001 and 2017. For a displacement taking place in year t we compute $\Delta Exp_{s,t-1}$ as the variation in the stock of robots in sector s between year $t-1$ and year $t-2$. Hence, we need robot data from 1999 to 2016. For all country-sector pairs the last year aailable in our dataset is 2018. *Sources*: IFR, own calculations.

Table A2: Balancing analysis, individual level (June 2001)

	Unconditional		Conditional	
	Coefficient	SE	Coefficient	SE
All workers				
Monthly earnings	16.9946***	0.1613	7.4951***	0.6111
Female	-0.0119***	0.0002	-0.0017***	0.0006
Foreign	-0.0016***	0.0001	0.0002	0.0001
Age	0.0177***	0.0040	-0.0228	0.0188
Middle- and low-skilled	0.0102***	0.0002	0.0036***	0.0004
Permanent contract	0.0160***	0.0002	0.0018**	0.0007
Temporary contract	-0.0029***	0.0002	-0.0000	0.0006
Self employed	-0.0069***	0.0001	-0.0000	0.0001
1-9 Employees	-0.0031***	0.0001	-0.0025***	0.0004
10-49 Employees	0.0007***	0.0001	-0.0046***	0.0006
50-249 Employees	0.0034***	0.0001	-0.0006	0.0006
More than 250 Employees	0.0088***	0.0001	0.0126***	0.0022
N	546,699		546,699	
Manufacturing workers				
Monthly earnings	13.4944***	0.2088	4.8333***	0.4895
Female	-0.0037***	0.0002	-0.0010	0.0007
Foreign	-0.0003***	0.0001	-0.0000	0.0001
Age	0.0192***	0.0054	-0.0437***	0.0165
Middle- and low-skilled	0.0032***	0.0002	0.0024***	0.0004
Permanent contract	0.0064***	0.0002	0.0006	0.0006
Temporary contract	-0.0023***	0.0002	-0.0002	0.0005
Self employed	-0.0037***	0.0001	-0.0000	0.0001
1-9 Employees	-0.0030***	0.0001	-0.0018***	0.0003
10-49 Employees	-0.0038***	0.0002	-0.0031***	0.0005
50-249 Employees	0.0010***	0.0002	-0.0011*	0.0006
More than 250 Employees	0.0148***	0.0002	0.0110***	0.0021
N	96,467		96,467	

Notes: Coefficients from 2SLS regressions of the respective transition characteristics on the change in robots exposure per 1,000 workers between 2001 and 2016 (instrumented with robot installations across industries in other European countries). The sample includes *all* workers with an on-going working spell on June 1, 2001. For workers with more than one spell in this month we selected the one with the highest earnings. All work-related characteristics refer to this spell only. The "Unconditional" column reports coefficient and standard error when the listed variables are regressed on predicted robot exposure and a constant, while column "Conditional" adds a series of standard control variables. The Control variables are wage, sex, foreign nationality, age, skill level (two categories), contract type (permanent, temporary, and self-employed), size of firm (four categories and missing), 1-digit sector dummies, NUTS2 area dummies and tenure. In each regression, all controls that are constructed from the dependent variable are not included in the estimation. Standard errors are clustered by 1-digit sector and NUTS3 area.
Sources: MCVL, IFR, INE and Eurostat, own calculations.

Table A3: Statistics on instruments

	R-squared	Overid.	F-statistic
Period 2001 - 2018			
Year and sector FE	0.251		
All 8 European countries	0.794	0.000	414.6
Italy, France, UK, Germany	0.763	0.000	420.8
Italy, France, UK	0.686	0.000	507.1
Sweden, Denmark, Finland, Norway	0.332	0.000	63.8
Japan	0.262		10.3
Average: all 8 European countries	0.610		281.5
Average: Italy, France, UK, Germany	0.614		293.9
Average: Italy, France, UK	0.563		245.7
Average: Sweden, Denmark, Finland, Norway	0.263		151.2
N	342	1,310,578	1,310,578
Period 2008 - 2018 (to include the US)			
Year and sector FE	0.124		
All 8 European countries	0.765	0.000	54.3
All 8 European countries + US	0.766	0.000	49.6
Italy, France, UK, Germany	0.725	0.000	108.5
Italy, France, UK, Germany, US	0.726	0.000	85.7
Italy, France, UK	0.449	0.000	72.5
Sweden, Denmark, Finland, Norway	0.176	0.000	18.8
Japan	0.125		6.5
US	0.164		1.1
Average: all 8 European countries	0.457		360.1
Average: Italy, France, UK, Germany	0.450		313.3
Average: Italy, France, UK	0.259		104.0
Average: Italy, France, UK, Germany, US	0.215		13.3
Average: Sweden, Denmark, Finland, Norway	0.141		51.4
N	209	459,177	459,177

Notes: The R-squared column refers to the regression of robot adoption in Spain over the instrument plus a battery of industry and year fixed effects. These regressions are performed at the country-year-industry level. The other 2 columns report post-estimation statistics, i.e. the p-value of the overidentification test and the Olea and Pflueger (2013) effective F-statistic, both performed on the full sample. In the overidentification test the null hypothesis is that the excluded instruments are all valid (i.e., uncorrelated with the error term and correctly excluded from the estimated equation). As for the issue of weak instruments, the rule of thumb is to consider the instrument valid when the Olea and Pflueger (2013) effective F-statistic is greater than 10.
Sources: MCVL and IFR, own calculations.

Table A4: Robustness checks - Lower pay (HS)

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	-0.0000	-0.0179***	0.0265***	0.0026	-0.0150	295,687
Subsamples						
Manufacturing	-0.0000	-0.0099***	0.0141***	0.0018	-0.0107	16,170
One transition	0.0017	-0.0104**	0.0246***	0.0028	-0.0056	135,644
Previous 6 months	0.0080*	-0.0075	0.0161***	0.0150***	-0.0151	163,214
4 months unemployed	0.0096*	-0.0081	0.0165***	0.0161***	-0.0175	87,067
24 months unemployed	0.0020	-0.0107***	0.0284***	0.0023	0.0001	96,413
Previous not automotive	0.0235***	-0.0204	0.0479***	0.0367***	-0.0414*	295,098
Only general regime	0.0001	-0.0177***	0.0264***	0.0027	-0.0149	290,756
Age 25-55	-0.0001	-0.0183***	0.0257***	0.0032	-0.0173*	255,055
Displaced in 2006-2017	-0.0139	-0.0398***	0.0106	-0.0067	-0.0480**	198,910
Displaced in 2001-2007	0.0012	-0.0119***	0.0237***	0.0029	-0.0090	132,169
Displaced in 2008-2017	-0.0195	-0.0674**	0.0095	-0.0068	-0.0617**	153,554
Spell length >= 180 days	-0.0051	-0.0139***	0.0112**	-0.0030	-0.0165**	179,829
Spell length >= 360 days	-0.0011	-0.0095**	0.0144**	0.0016	-0.0176**	113,446
IFR aggregation schemes						
15 Groups	-0.0043	-0.0228***	0.0291***	-0.0027	-0.0122	295,687
17 Groups	-0.0029	-0.0231***	0.0271***	-0.0002	-0.0177*	295,687
20 Groups	0.0002	-0.0173***	0.0261***	0.0029	-0.0154	295,687
Migration						
Non-neighbouring NUTS3	-0.0000	-0.0179***	0.0267***	0.0012	-0.0128	295,687
Fixed effects						
Add Current spell FE	0.0004	-0.0123***	0.0190***	0.0030	-0.0143	295,687
NUTS2(Prev)*Year Exit	0.0001	-0.0172***	0.0258***	0.0026	-0.0140	295,687
NUTS2*Year Entry	0.0004	-0.0176***	0.0270***	0.0028	-0.0136	295,687
Sector FE and ΔSec						
1-dig ΔIFR15(2-dig)	-0.0012	-0.0243***	0.0141***	0.0016	-0.0176*	295,687
IFR15(1-dig) Δ1-dig	0.0049	-0.0161***	0.0289***	0.0076	-0.0103	295,687
IFR15(1-dig) ΔIFR15(2-dig)	0.0040	-0.0211***	0.0174***	0.0070	-0.0127	295,687
IFR15(2-dig) Δ1-dig	0.0051	-0.0154***	0.0284***	0.0077	-0.0096	295,687
IFR15(2-dig) ΔIFR15(2-dig)	0.0042	-0.0196***	0.0170***	0.0072	-0.0121	295,687
IFR15(2-dig) ΔIFR15(2-dig)	0.0038	-0.0223***	0.0169***	0.0067	-0.0124	295,687

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.
Sources: MCVL and IFR, own calculations.

Table A5: Robustness checks - Lower pay (MLS)

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0213***	0.0058***	0.0332***	0.0202***	0.0306***	1,035,553
Subsamples						
Manufacturing	0.0198***	0.0091***	0.0282***	0.0187***	0.0300***	122,131
One transition	0.0210***	0.0061**	0.0346***	0.0200***	0.0309***	370,492
Previous 6 months	0.0265***	0.0182***	0.0301***	0.0260***	0.0301***	674,077
4 months unemployed	0.0286***	0.0195***	0.0318***	0.0280***	0.0333***	346,976
24 months unemployed	0.0074**	-0.0047	0.0297***	0.0054*	0.0368***	163,393
Previous not automotive	0.0246***	0.0002	0.0386***	0.0242***	0.0269***	1,029,600
Only general regime	0.0211***	0.0057***	0.0331***	0.0201***	0.0308***	993,618
Age 25-55	0.0194***	0.0035*	0.0324***	0.0187***	0.0264***	807,476
Displaced in 2006-2017	0.0311***	0.0028	0.0492***	0.0305***	0.0355***	634,641
Displaced in 2001-2007	0.0191***	0.0058***	0.0299***	0.0182***	0.0283***	541,925
Displaced in 2008-2017	0.0366***	0.0086	0.0501***	0.0362***	0.0392***	462,348
Spell length >= 180 days	0.0218***	0.0103***	0.0361***	0.0206***	0.0311***	423,153
Spell length >= 360 days	0.0189***	0.0089**	0.0344***	0.0169***	0.0385***	201,196
IFR aggregation schemes						
15 Groups	0.0234***	0.0054***	0.0377***	0.0222***	0.0353***	1,035,553
17 Groups	0.0213***	0.0053***	0.0336***	0.0202***	0.0318***	1,035,553
20 Groups	0.0212***	0.0058***	0.0330***	0.0202***	0.0304***	1,035,553
Migration						
Non-neighbouring NUTS3	0.0213***	0.0057***	0.0332***	0.0212***	0.0224***	1,035,553
Fixed effects						
Add Current spell FE	0.0205***	0.0113***	0.0276***	0.0195***	0.0301***	1,035,553
NUTS2(Prev)*Year Exit	0.0211***	0.0058***	0.0328***	0.0201***	0.0298***	1,035,553
NUTS2*Year Entry	0.0219***	0.0064***	0.0337***	0.0208***	0.0311***	1,035,553
Sector FE and ΔSec						
1-dig ΔIFR15(2-dig)	0.0206***	-0.0044*	0.0283***	0.0196***	0.0304***	1,035,553
IFR15(1-dig) Δ1-dig	0.0023	-0.0130***	0.0134***	0.0011	0.0118***	1,035,553
IFR15(1-dig) ΔIFR15(2-dig)	0.0021	-0.0222***	0.0096***	0.0009	0.0120***	1,035,553
IFR15(2-dig) Δ1-dig	0.0022	-0.0132***	0.0135***	0.0010	0.0120***	1,035,553
IFR15(2-dig) ΔIFR15(2-dig)	0.0021	-0.0226***	0.0097***	0.0008	0.0121***	1,035,553
IFR15(2-dig) ΔIFR15(2-dig)	0.0022	-0.0235***	0.0093***	0.0010	0.0124***	1,035,553

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.
Sources: MCVL and IFR, own calculations.

Table A6: Robustness checks - Ratio of new pay over previous one ($\times$100) (HS)

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	-0.4817**	0.4081**	-1.8060***	-0.6247***	0.3285	295,687
Subsamples						
Manufacturing	-0.3574**	0.1643	-1.1059***	-0.5049***	0.4854	16,170
One transition	-0.6482**	0.1213	-2.0949***	-0.6846**	-0.4116	135,644
Previous 6 months	-1.0053***	0.8165	-1.9510***	-1.4520***	0.4774	163,214
4 months unemployed	-1.3260**	0.2063	-1.9250***	-1.6230***	-0.0907	87,067
24 months unemployed	-0.3863**	0.2929*	-1.7898***	-0.3406*	-0.7145	96,413
Previous not automotive	-1.6909***	0.3267	-2.8123***	-1.9662***	-0.3364	295,098
Only general regime	-0.4851**	0.3902*	-1.7809***	-0.6315***	0.3426	290,756
Age 25-55	-0.4753**	0.4151*	-1.7303***	-0.6841***	0.6339	255,055
Displaced in 2006-2017	-0.3286	1.6407**	-2.1885***	-0.4648	0.3197	198,910
Displaced in 2001-2007	-0.4690**	0.2385	-1.6792***	-0.6610***	0.7271	132,169
Displaced in 2008-2017	-0.4467	2.4071*	-2.1702**	-0.5258	-0.1831	153,554
Spell length >= 180 days	-0.2424	0.2521	-1.1493**	-0.3118	0.1424	179,829
Spell length >= 360 days	-0.3574	0.1519	-1.3077**	-0.3846	-0.1960	113,446
IFR aggregation schemes						
15 Groups	-0.5463**	0.4722**	-2.3769***	-0.6387**	-0.0694	295,687
17 Groups	-0.4930**	0.4352**	-1.8693***	-0.6524***	0.3740	295,687
20 Groups	-0.4688**	0.3935**	-1.7504***	-0.6150***	0.3586	295,687
Migration						
Non-neighbouring NUTS3	-0.4812**	0.4112**	-1.8091***	-0.5902***	0.6943	295,687
Fixed effects						
Add Current spell FE	-0.5000***	0.0576	-1.3185***	-0.6401***	0.2922	295,687
NUTS2(Prev)*Year Exit	-0.5960***	0.2301	-1.8208***	-0.7164***	0.0844	295,687
NUTS2*Year Entry	-0.5161**	0.3810*	-1.8440***	-0.6576***	0.2860	295,687
Sector FE and ΔSec						
1-dig ΔIFR15(2-dig)	-0.4531**	0.4105**	-1.0272***	-0.6036***	0.3999	295,687
IFR15(1-dig) Δ1-dig	-0.5207*	0.5628*	-1.7571***	-0.6674**	0.2943	295,687
IFR15(1-dig) ΔIFR15(2-dig)	-0.5014	0.4487	-1.0077***	-0.6563**	0.3590	295,687
IFR15(2-dig) Δ1-dig	-0.5347*	0.4878	-1.7012***	-0.6737**	0.2382	295,687
IFR15(2-dig) ΔIFR15(2-dig)	-0.5145	0.3238	-0.9611***	-0.6640**	0.3166	295,687
IFR15(2-dig) ΔIFR15(2-dig)	-0.5022	0.4416	-0.9758***	-0.6508**	0.3242	295,687

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.

Sources: MCVL and IFR, own calculations.

Table A7: Robustness checks - Ratio of new pay over previous one ($\times 100$) (MLS)

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	-1.9237***	-0.4439***	-3.0613***	-1.7958***	-3.0930***	1,035,553
Subsamples						
Manufacturing	-1.7705***	-0.7151***	-2.5855***	-1.6364***	-2.9858***	122,131
One transition	-1.9135***	-0.4550**	-3.2413***	-1.7865***	-3.1124***	370,492
Previous 6 months	-2.5410***	-1.0706***	-3.1645***	-2.4321***	-3.3098***	674,077
4 months unemployed	-2.8071***	-0.9371***	-3.4506***	-2.6843***	-3.6957***	346,976
24 months unemployed	-0.8346***	0.1757	-2.6909***	-0.6446***	-3.5249***	163,393
Previous not automotive	-1.5507***	1.2386***	-3.1524***	-1.2540***	-3.3432***	1,029,600
Only general regime	-1.9082***	-0.4599***	-3.0292***	-1.7825***	-3.0768***	993,618
Age 25-55	-1.7936***	-0.3053**	-3.0034***	-1.6619***	-2.9511***	807,476
Displaced in 2006-2017	-2.7694***	0.5153	-4.8640***	-2.5919***	-4.0023***	634,641
Displaced in 2001-2007	-1.7664***	-0.6082***	-2.7048***	-1.6691***	-2.7271***	541,925
Displaced in 2008-2017	-3.2686***	0.7942	-5.2253***	-3.0550***	-4.4941***	462,348
Spell length >= 180 days	-2.0027***	-0.7753***	-3.5340***	-1.8503***	-3.2851***	423,153
Spell length >= 360 days	-1.7899***	-0.6562***	-3.5356***	-1.6085***	-3.5947***	201,196
IFR aggregation schemes						
15 Groups	-2.2198***	-0.3946***	-3.6705***	-2.0841***	-3.4838***	1,035,553
17 Groups	-1.9608***	-0.4356***	-3.1382***	-1.8346***	-3.1235***	1,035,553
20 Groups	-1.9127***	-0.4435***	-3.0420***	-1.7855***	-3.0761***	1,035,553
Migration						
Non-neighbouring NUTS3	-1.9216***	-0.4433***	-3.0581***	-1.8853***	-2.7995***	1,035,553
Fixed effects						
Add Current spell FE	-1.8446***	-0.8546***	-2.6100***	-1.7122***	-3.0549***	1,035,553
NUTS2(Prev)*Year Exit	-1.9165***	-0.4485***	-3.0439***	-1.7954***	-3.0257***	1,035,553
NUTS2*Year Entry	-1.9754***	-0.4947***	-3.1112***	-1.8479***	-3.1384***	1,035,553
Sector FE and ΔSec						
1-dig ΔIFR15(2-dig)	-1.9251***	0.2257	-2.5849***	-1.7972***	-3.0944***	1,035,553
IFR15(1-dig) Δ1-dig	0.0490	1.5143***	-1.0202***	0.1972	-1.1268***	1,035,553
IFR15(1-dig) ΔIFR15(2-dig)	0.0495	2.1182***	-0.5896***	0.1976	-1.1258***	1,035,553
IFR15(2-dig) Δ1-dig	0.0538	1.5219***	-1.0175***	0.2033	-1.1332***	1,035,553
IFR15(2-dig) ΔIFR15(2-dig)	0.0545	2.1466***	-0.5918***	0.2040	-1.1319***	1,035,553
IFR15(2-dig) ΔIFR15(2-dig)	0.0562	2.1700***	-0.5212***	0.2056	-1.1298***	1,035,553

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.
Sources: MCVL and IFR, own calculations.

Table A8: Robustness checks - Lower qualification (HS)

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0088*	0.0068	0.0119	0.0084	0.0111	295,687
Subsamples						
Manufacturing	0.0033	-0.0049	0.0151**	0.0039	-0.0002	16,170
One transition	-0.0003	-0.0001	-0.0007	-0.0001	-0.0021	135,644
Previous 6 months	0.0018	0.0267**	-0.0111	0.0025	-0.0004	163,214
4 months unemployed	0.0006	0.0198	-0.0070	0.0027	-0.0083	87,067
24 months unemployed	0.0002	-0.0019	0.0044	-0.0004	0.0040	96,413
Previous not automotive	0.0447***	0.0677***	0.0319**	0.0506***	0.0154	295,098
Only general regime	0.0084*	0.0060	0.0119	0.0078	0.0115	290,756
Age 25-55	0.0098**	0.0061	0.0149*	0.0099*	0.0092	255,055
Displaced in 2006-2017	-0.0001	0.0375**	-0.0357***	-0.0016	0.0069	198,910
Displaced in 2001-2007	0.0058	-0.0010	0.0173**	0.0068	-0.0009	132,169
Displaced in 2008-2017	0.0031	0.0640***	-0.0336**	-0.0008	0.0161	153,554
Spell length >= 180 days	0.0027	0.0035	0.0013	0.0018	0.0080	179,829
Spell length >= 360 days	-0.0005	-0.0005	-0.0005	0.0003	-0.0055	113,446
IFR aggregation schemes						
15 Groups	-0.0011	0.0049	-0.0118*	-0.0042	0.0153*	295,687
17 Groups	0.0047	0.0045	0.0051	0.0043	0.0069	295,687
20 Groups	0.0089*	0.0066	0.0125	0.0085	0.0112	295,687
Migration						
Non-neighbouring NUTS3	0.0087*	0.0069	0.0115	0.0079	0.0176*	295,687
Fixed effects						
Add Current spell FE	0.0083*	0.0018	0.0178**	0.0079	0.0107	295,687
NUTS2(Prev)*Year Exit	0.0083*	0.0058	0.0119	0.0080	0.0099	295,687
NUTS2*Year Entry	0.0084*	0.0057	0.0123	0.0079	0.0112	295,687
Sector FE and ΔSec						
1-dig ΔIFR15(2-dig)	0.0053	0.0020	0.0075	0.0055	0.0042	295,687
IFR15(1-dig) Δ1-dig	0.0169**	0.0153**	0.0188**	0.0166**	0.0188**	295,687
IFR15(1-dig) ΔIFR15(2-dig)	0.0143**	0.0113**	0.0159**	0.0146**	0.0124	295,687
IFR15(2-dig) Δ1-dig	0.0167**	0.0139**	0.0199**	0.0165**	0.0177**	295,687
IFR15(2-dig) ΔIFR15(2-dig)	0.0142**	0.0101*	0.0164**	0.0147**	0.0115	295,687
IFR15(2-dig) ΔIFR15(2-dig)	0.0132**	0.0070	0.0163**	0.0136**	0.0109	295,687

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.
Sources: MCVL and IFR, own calculations.

Table A9: Robustness checks - Lower qualification (MLS)

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0102***	0.0043***	0.0148***	0.0109***	0.0040*	1,035,553
Subsamples						
Manufacturing	0.0094***	0.0041***	0.0135***	0.0094***	0.0094***	122,131
One transition	0.0093***	0.0014	0.0165***	0.0102***	0.0016	370,492
Previous 6 months	0.0129***	0.0129***	0.0129***	0.0142***	0.0035	674,077
4 months unemployed	0.0137***	0.0146***	0.0134***	0.0145***	0.0076**	346,976
24 months unemployed	-0.0010	-0.0045***	0.0055*	-0.0011	0.0013	163,393
Previous not automotive	0.0025	0.0010	0.0034	0.0052**	-0.0138***	1,029,600
Only general regime	0.0102***	0.0036***	0.0154***	0.0108***	0.0047**	993,618
Age 25-55	0.0088***	0.0027**	0.0137***	0.0096***	0.0020	807,476
Displaced in 2006-2017	0.0126***	0.0085***	0.0152***	0.0150***	-0.0039	634,641
Displaced in 2001-2007	0.0102***	0.0036***	0.0156***	0.0106***	0.0065***	541,925
Displaced in 2008-2017	0.0117**	0.0089**	0.0130**	0.0144***	-0.0040	462,348
Spell length >= 180 days	0.0069***	0.0049***	0.0093***	0.0069***	0.0064**	423,153
Spell length >= 360 days	0.0045***	0.0022	0.0081***	0.0045***	0.0048	201,196
IFR aggregation schemes						
15 Groups	0.0100***	0.0038***	0.0149***	0.0108***	0.0021	1,035,553
17 Groups	0.0103***	0.0040***	0.0152***	0.0109***	0.0045**	1,035,553
20 Groups	0.0102***	0.0043***	0.0147***	0.0108***	0.0041*	1,035,553
Migration						
Non-neighbouring NUTS3	0.0102***	0.0042***	0.0148***	0.0107***	-0.0018	1,035,553
Fixed effects						
Add Current spell FE	0.0092***	0.0057***	0.0118***	0.0097***	0.0040**	1,035,553
NUTS2(Prev)*Year Exit	0.0100***	0.0041***	0.0145***	0.0107***	0.0036*	1,035,553
NUTS2*Year Entry	0.0102***	0.0042***	0.0148***	0.0108***	0.0044**	1,035,553
Sector FE and ΔSec						
1-dig ΔIFR15(2-dig)	0.0095***	-0.0048***	0.0139***	0.0102***	0.0038*	1,035,553
IFR15(1-dig) Δ1-dig	0.0017	-0.0041***	0.0059***	0.0024	-0.0038*	1,035,553
IFR15(1-dig) ΔIFR15(2-dig)	0.0015	-0.0119***	0.0056***	0.0021	-0.0036	1,035,553
IFR15(2-dig) Δ1-dig	0.0017	-0.0041***	0.0060***	0.0024	-0.0037	1,035,553
IFR15(2-dig) ΔIFR15(2-dig)	0.0015	-0.0119***	0.0056***	0.0021	-0.0035	1,035,553
IFR15(2-dig) ΔIFR15(2-dig)	0.0017	-0.0123***	0.0055***	0.0023	-0.0032	1,035,553

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.

Sources: MCVL and IFR, own calculations.

Table A10: Robustness checks - Temporary contract (HS)

	ΔExp	$\Delta Sec=0$	$\Delta Sec=1$	$\Delta NUTS=0$	$\Delta NUTS=1$	N
Baseline	0.0003	-0.0034	0.0080	0.0008	-0.0028	96,413
Subsamples						
Manufacturing	-0.0012	-0.0056*	0.0075	-0.0000	-0.0095	9,397
One transition	-0.0022	-0.0053	0.0047	-0.0010	-0.0111	67,141
Previous 6 months	-0.0113**	-0.0049	-0.0147**	-0.0092	-0.0190*	42,344
4 months unemployed	-0.0117*	-0.0124	-0.0115	-0.0086	-0.0246	26,587
24 months unemployed	0.0003	-0.0034	0.0080	0.0008	-0.0028	96,413
Previous not automotive	0.0317***	0.0296***	0.0330***	0.0321***	0.0291	96,016
Only general regime	0.0001	-0.0039	0.0082	0.0003	-0.0019	95,036
Age 25-55	0.0017	-0.0030	0.0109	0.0025	-0.0034	88,262
Displaced in 2006-2017	0.0128	0.0168	0.0081	0.0101	0.0298	69,220
Displaced in 2001-2007	-0.0012	-0.0033	0.0038	0.0007	-0.0153**	37,824
Displaced in 2008-2017	0.0092	0.0136	0.0061	0.0036	0.0338	54,547
Spell length >= 180 days	-0.0018	-0.0031	0.0013	-0.0016	-0.0033	79,694
Spell length >= 360 days	-0.0005	-0.0021	0.0034	0.0001	-0.0041	63,877
IFR aggregation schemes						
15 Groups	-0.0080**	-0.0072**	-0.0100	-0.0081**	-0.0071	96,413
17 Groups	-0.0046	-0.0072**	0.0007	-0.0038	-0.0104	96,413
20 Groups	0.0005	-0.0034	0.0086	0.0010	-0.0030	96,413
Migration						
Non-neighbouring NUTS3	0.0003	-0.0035	0.0081	0.0016	-0.0136*	96,413
Fixed effects						
Add Current spell FE	0.0015	-0.0028	0.0103	0.0020	-0.0021	96,413
NUTS2(Prev)*Year Exit	-0.0000	-0.0033	0.0067	0.0005	-0.0035	96,413
NUTS2*Year Entry	0.0007	-0.0030	0.0080	0.0011	-0.0023	96,413
Sector FE and ΔSec						
1-dig ΔIFR15(2-dig)	-0.0017	-0.0078***	0.0042	-0.0011	-0.0061	96,413
IFR15(1-dig) Δ1-dig	0.0050	-0.0002	0.0131	0.0054	0.0021	96,413
IFR15(1-dig) ΔIFR15(2-dig)	0.0033	-0.0041	0.0090	0.0040	-0.0014	96,413
IFR15(2-dig) Δ1-dig	0.0050	-0.0006	0.0135	0.0054	0.0021	96,413
IFR15(2-dig) ΔIFR15(2-dig)	0.0035	-0.0040	0.0091	0.0041	-0.0013	96,413
IFR15(2-dig) ΔIFR15(2-dig)	0.0024	-0.0048	0.0077	0.0031	-0.0021	96,413

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.
Sources: MCVL and IFR, own calculations.

Table A11: Robustness checks - Temporary contract (MLS)

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	-0.0099***	-0.0206***	0.0096*	-0.0110***	0.0051	163,393
Subsamples						
Manufacturing	-0.0082***	-0.0182***	0.0092	-0.0093***	0.0064	28,152
One transition	-0.0095***	-0.0215***	0.0110**	-0.0104***	0.0022	123,575
Previous 6 months	-0.0005	0.0040	-0.0023	-0.0009	0.0025	89,925
4 months unemployed	0.0018	0.0017	0.0018	0.0014	0.0041	55,626
24 months unemployed	-0.0099***	-0.0206***	0.0096*	-0.0110***	0.0051	163,393
Previous not automotive	0.0116	-0.0174*	0.0331***	0.0139	-0.0090	161,980
Only general regime	-0.0094***	-0.0201***	0.0105*	-0.0106***	0.0086	157,361
Age 25-55	-0.0095***	-0.0199***	0.0094*	-0.0106***	0.0064	140,001
Displaced in 2006-2017	-0.0126**	-0.0293***	0.0069	-0.0140**	0.0016	117,970
Displaced in 2001-2007	-0.0072**	-0.0155***	0.0104	-0.0079***	0.0039	62,335
Displaced in 2008-2017	-0.0078	-0.0217	0.0010	-0.0092	0.0041	92,477
Spell length >= 180 days	-0.0083***	-0.0139***	0.0044	-0.0095***	0.0091	124,828
Spell length >= 360 days	-0.0075***	-0.0114***	0.0013	-0.0077***	-0.0048	92,828
IFR aggregation schemes						
15 Groups	-0.0137***	-0.0216***	0.0027	-0.0152***	0.0085	163,393
17 Groups	-0.0105***	-0.0216***	0.0104*	-0.0118***	0.0083	163,393
20 Groups	-0.0097***	-0.0203***	0.0098*	-0.0108***	0.0051	163,393
Migration						
Non-neighbouring NUTS3	-0.0100***	-0.0208***	0.0099*	-0.0102***	-0.0017	163,393
Fixed effects						
Add Current spell FE	-0.0089***	-0.0175***	0.0065	-0.0098***	0.0032	163,393
NUTS2(Prev)*Year Exit	-0.0095***	-0.0200***	0.0094*	-0.0105***	0.0045	163,393
NUTS2*Year Entry	-0.0097***	-0.0205***	0.0095*	-0.0108***	0.0053	163,393
Sector FE and ΔSec						
1-dig ΔIFR15(2-dig)	-0.0109***	-0.0294***	0.0072	-0.0119***	0.0028	163,393
IFR15(1-dig) Δ1-dig	0.0030	-0.0097**	0.0222***	0.0017	0.0184***	163,393
IFR15(1-dig) ΔIFR15(2-dig)	0.0031	-0.0173***	0.0205***	0.0019	0.0172***	163,393
IFR15(2-dig) Δ1-dig	0.0031	-0.0101**	0.0232***	0.0017	0.0195***	163,393
IFR15(2-dig) ΔIFR15(2-dig)	0.0033	-0.0174***	0.0209***	0.0021	0.0180***	163,393
IFR15(2-dig) ΔIFR15(2-dig)	0.0039	-0.0177***	0.0210***	0.0025	0.0201***	163,393

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.
Sources: MCVL and IFR, own calculations.

Table A12: Robustness checks - ETT firm (HS)

	ΔExp	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0025	0.0040**	-0.0061*	292,476
Subsamples				
Manufacturing	0.0029	0.0039*	-0.0030	16,170
One transition	0.0003	0.0014	-0.0072*	135,772
Previous 6 months	0.0020	0.0057	-0.0103**	161,843
4 months unemployed	0.0060	0.0095*	-0.0087**	86,413
24 months unemployed	0.0007	0.0010	-0.0011	96,398
Previous not automotive	0.0106***	0.0152***	-0.0121	291,887
Only general regime	0.0025	0.0040**	-0.0061*	287,554
Age 25-55	0.0031*	0.0044**	-0.0038	252,485
Displaced in 2006-2017	0.0031	0.0066	-0.0135**	197,062
Displaced in 2001-2007	0.0020	0.0031	-0.0048	130,195
Displaced in 2008-2017	0.0054	0.0106	-0.0117	152,346
Spell length >= 180 days	0.0006	0.0005	0.0009	179,093
Spell length >= 360 days	0.0002	0.0002	0.0004	113,219
IFR aggregation schemes				
15 Groups	0.0012	0.0028	-0.0068**	292,476
17 Groups	0.0018	0.0036*	-0.0080**	292,476
20 Groups	0.0024	0.0038*	-0.0061*	292,476
Migration				
Non-neighbouring NUTS3	0.0025	0.0036*	-0.0092**	292,476
Fixed effects				
Add Current spell FE	0.0012	0.0026*	-0.0067**	292,476
NUTS2(Prev)*Year Exit	0.0025	0.0040*	-0.0059*	292,476
NUTS2*Year Entry	0.0025	0.0041**	-0.0062*	292,476
Sector				
IFR15(1-dig)	-0.0001	0.0014	-0.0087**	292,476
IFR15(2-dig)	-0.0006	0.0010	-0.0097**	292,476

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.
Sources: MCVL and IFR, own calculations.

Table A13: Robustness checks - ETT firm (MLS)

	ΔExp	$\Delta NUTS=0$	$\Delta NUTS=1$	N
Baseline	0.0121***	0.0131***	0.0030	966,016
Subsamples				
Manufacturing	0.0097***	0.0101***	0.0061**	122,131
One transition	0.0125***	0.0131***	0.0067*	361,540
Previous 6 months	0.0145***	0.0159***	0.0040	635,979
4 months unemployed	0.0147***	0.0160***	0.0051	330,697
24 months unemployed	0.0017	0.0013	0.0079	163,150
Previous not automotive	0.0104***	0.0126***	-0.0032	960,063
Only general regime	0.0120***	0.0130***	0.0031	925,678
Age 25-55	0.0125***	0.0132***	0.0061**	758,092
Displaced in 2006-2017	0.0177***	0.0199***	0.0026	596,399
Displaced in 2001-2007	0.0117***	0.0124***	0.0042	496,979
Displaced in 2008-2017	0.0190***	0.0218***	0.0024	438,343
Spell length >= 180 days	0.0035***	0.0036***	0.0024	413,615
Spell length >= 360 days	0.0003	0.0006	-0.0017	199,458
IFR aggregation schemes				
15 Groups	0.0134***	0.0147***	0.0013	966,016
17 Groups	0.0128***	0.0139***	0.0026	966,016
20 Groups	0.0119***	0.0129***	0.0029	966,016
Migration				
Non-neighbouring NUTS3	0.0121***	0.0128***	-0.0050**	966,016
Fixed effects				
Add Current spell FE	0.0072***	0.0080***	-0.0002	966,016
NUTS2(Prev)*Year Exit	0.0120***	0.0130***	0.0030	966,016
NUTS2*Year Entry	0.0120***	0.0130***	0.0032	966,016
Sector				
IFR15(1-dig)	-0.0005	0.0006	-0.0092***	966,016
IFR15(2-dig)	-0.0007	0.0004	-0.0090***	966,016

Notes: Two-stage least squares (2SLS) IV regressions, where Spanish robot exposure is instrumented with the average robot installations across industries in 4 other European countries. Each block reports the estimate for the effect of the predicted change in robot exposure per 1000 workers on the dependent variable. All regressions are performed separately by skill group and include the full battery controls described in Section 4 plus a constant. Standard errors are clustered by province, 2-digit sector and year of dismissal.
Sources: MCVL and IFR, own calculations.