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Automation and Adjustment in Europe: A Comparative Study of the Robot Revolution

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Author(s)	:	Chinchih Chen (Oxford Martin School), Carl Benedikt Frey (Oxford Martin School)
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Description of deliverable (100 words)

Deliverable 1.5 examines how industrial robots have shaped employment patterns in nine European countries: Denmark, Finland, France, Germany, Norway, Spain, Sweden, Italy and United Kingdom. We find that robots reduced employment in the manufacturing sector in all countries in our sample. The impact of robots on total employment in local labour markets, however, is more ambiguous. While local labour markets experienced significant employment losses in Italy, Norway and the United Kingdom, we find no statistically significant impact of robots on employment in France, Germany, Sweden, Denmark, Finland and Spain. In most of these countries job losses were seemingly offset by employment gains in other sectors of the economy.

Summary

Much popular commentary in recent years has centred on the question of whether robots destroy or create jobs. Against this backdrop, we provide the first comprehensive assessment of the impact of robots on labour markets across Europe. While we find that robots have been one of the drivers of deindustrialization across European economies, some countries have fared better in terms of creating new jobs in other sectors of the economy. To what extent robots reduce employment plausibly depends on both labour market conditions and institutions. For example, while the Scandinavian countries have similar labour market institutions, they have adjusted differentially to the robot revolution. Overall, our findings imply that there is no “one” future of work: how labour markets adjust to automation will depend on educational systems, tax regimes, collective bargaining, macroeconomic shocks, just to name a few. We leave disentangling the relative importance of these factors for future research.

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1. Introduction

How have workers in Europe fared from automation in recent decades? While some see robots as a harbinger of technological unemployment (Ford, 2015), the evidence is mixed so far. In the United States and in the United Kingdom, there is compelling evidence that industrial robots have reduced employment (Acemoglu and Restrepo, 2020; Chen and Frey, 2020), but in Germany jobs lost to robots in manufacturing were offset by jobs gained in other sectors (Dauth *et al*., 2017). Thus, while robots reduce the demand for labour in the production of manufactured goods, they also boost productivity and create new tasks (Acemoglu and Restrepo, 2018). Which effect dominates is likely to depend on specific labour market characteristics, such as skills endowments, labour market institutions, tax regimes, and patterns of specialization.

In this paper, we examine the employment effects of industrial robots in nine European countries: Denmark, Finland, France, Germany, Norway, Spain, Sweden, Italy and the United Kingdom. To our knowledge, this constitutes the first comparative assessment of the impacts of automation across local labour markets in Europe. For our analysis, we construct a measure of exposure to automation using data from the International Federation of Robotics (IFR), which provides annual robot counts across industries and countries. Thus, as in Acemoglu and Restrepo (2020), the variation in our automation measure stems from the fact that local markets within each country specialize in different industries, making some places more exposed to automation than others. Following Autor *et al*. (2013), showing that Chinese imports have had dramatic negative impacts on employment in local labour in the United States, we also report the effects of Chinese imports across European countries for comparison. For this analysis, we use the trade data from the UN Comtrade database.

A concern with our empirical strategy is that the adoption of robots in a given industry might be related to other confounding variables affecting that particular industry. To mitigate such concerns, we use the industry-level operational robot stock of other high-income countries as instruments for a country's industry exposure.[1] Our IV estimates show that the

[1] In other words, we follow the approach of Acemoglu and Restrepo (2020), examining the impact of robots on jobs in local labour markets across the United States. Our approach is also similar to that of Autor *et al*. (2013) and Bloom *et al*. (2015), investigating the impact of Chinese import competition on employment across geographies.

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impact of robots on employment is highly heterogeneous across Europe. Turning first to manufacturing sector, we find that robots have a consistently negative impact on manufacturing jobs across all countries, though some coefficients are imprecisely estimated. This stands in contrast to imports from China, which have a positive impact on manufacturing employment in some Nordic countries, notably in Finland, while reducing employment in Italy, Spain and the United Kingdom.

The impact of robots beyond the manufacturing sector is more ambiguous. Though our analysis draws upon different data sources provided by national statistics offices for slightly different periods of time, and cross-country comparisons thus need to be made with caution, some patterns are nonetheless noteworthy. While local labour markets with a greater exposure to robots experienced significant employment losses in Italy, Norway and the United Kingdom, we find no statistically significant impact of robots on employment in France, Germany, Denmark, Finland and Spain. Quantitatively, our baseline estimate suggests that the adoption of one additional robot per thousand workers in a given city reduced its employment-to-population ratio by 0.42 percentage points relative to other areas in Italy, by 3.22 percentage points in Norway, and by 0.94 percentage point in the United Kingdom. We note that the employment effects of robots in Norway and the United Kingdom are significantly larger in magnitude than previously reported estimates for the United States and other European countries (Acemoglu and Restrepo, 2020; Dauth *et al*., 2017; Dottori, 2020). We attribute these large negative employment effects to the relatively small robot stock in both countries, which implies that robot adoption is subject to diminishing returns in production. Such an interpretation is consistent with Graetz and Michaels (2018), showing that the productivity effect of one additional robot declines as the robot stock expands.

Our findings add to a growing body of work, showing that the impact of robots on jobs has been highly heterogeneous across countries. For example, while there is evidence that robots have reduced employment in the United States (Acemoglu and Restrepo, 2020), firm-level evidence from the Netherlands even suggests that robot adoption is associated with faster employment growth (Bessen *et al*., 2020). More broadly, examining seventeen countries, Graetz and Michaels (2018) find that robots had no significant effect on total hours worked on average. While we are unable to disentangle the factors underpinning the heterogeneity in our sample, we also note some common patterns. Across the investigated countries, robots

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seem to have reduced employment in the manufacturing sector, though we note that, in some cases, the effects are not statistically significant. We also note that the adverse employment consequences of robots are primarily borne by young and middle aged workers, and unskilled men, with some exceptions. Finally, we note that unlike other computer technologies, which have complemented skilled labour (Autor and Dorn, 2013; Autor *et al*., 2003), the direct employment effect of robots seems to have been replacing for unskilled labour without increasing the demand for skilled workers. The remainder of this paper is structured as follows. Section 2 describes our data sources. In section 3, we outline our empirical strategy and key findings. We also provide a battery of robustness checks. Finally, in section 4, we provide some conclusions.

2. Measurement and Data

2.1 Robots

To measure the impact of advanced robotics on local labour markets, we collect data on industrial robots from the International Federation of Robotics (IFR), which compiles annual counts of robots used by country and industry from 1993 onwards. Industrial robots are defined as 'automatically controlled, re-programmable, and multipurpose' machines that are autonomous (i.e., does not require a human operator) and that can flexibly be adapted to perform a variety of tasks (IFR, 2014). The robot counts are based on consolidated data provided by nearly all industrial robot suppliers worldwide to the IFR.[2] The main limitation of the IFR data is this does not incorporate other automation technologies, like software and artificial intelligence. Nevertheless, it provides a useful source of consistently defined information on investments in industrial automation as demonstrated by the existing literature (Frey *et al*., 2018; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020).

Based on IFR's industrial classification, we construct a dataset on the use of robots for 12 disaggregated manufacturing industries: foods and beverages; textiles (including apparel); woods and furniture; paper and printing; plastic and chemicals; minerals, glass, and ceramics; basic metals and metal products; industrial machinery; electronics; automotive; other transport equipment; and miscellaneous manufacturing. Outside of manufacturing, we

[2] However, if some countries, like Japan, have their own surveys or calculations of the operational robot stock, the IFR uses those figures.

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consolidate the data into six broad industries: agriculture, forestry and fishing; mining; utilities; construction; education, research and development; and services. We note that there are still some robots that are not classified into one of the 18 industries. For example, more than 50% of robots in Denmark are unspecified before 2000 as well as about 5% unclassified robots in Spain. To account up for this shortcoming, we assign unspecified robots to each industry in the proportions that the remainder of the robot stock is allocated in each year.[3]

Figure 1 plots the evolution of the robot intensity in production for Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden and the United Kingdom (Panel A), as well as changes in the operational robot stock by industry (Panel B). We note that Germany has the highest robot intensity throughout the investigated period, although some countries have been catching up, while others have fallen behind. For example, in 1995, the German robot intensity is around 1.5 robots per thousand workers and 0.34 in the United Kingdom. By 2007, the German robot intensity has increased above 4 while it was still a mere 0.6 in the United Kingdom. To be sure, some of these differences can be explained by different patterns of specialization. As shown in Panel B, the European automotive industry has adopted most robots over the past two decades, followed chemicals, metals, foods, machinery and electronics. The use of robots is much less common in other industries, especially in non-manufacturing sectors. To address the potential bias of our results being driven by events in the automotive industry, we examine the effect of automotive and non-automotive robot adoption on local labour market in the robustness section.

Next, to measure the industry-level variation at different time periods, we follow Acemoglu and Restrepo (2020) and construct adjusted penetration of robots (APR), which is the change in robot installation per thousand workers with an adjustment for the industry-wide output expansion. We combine the IFR data with employee counts and real gross output (2007=100) in the country-industry level from EUKLEMS dataset (November 2009 Release, updated March 2011; see van Ark and Jager, 2017). In our study, the baseline measure of the adjusted penetration of robots is between t0 and t1 for each country as in equation 1.

[3] Robots for Denmark between 1993-1996 are allocated manually using the 1996 industry composition.

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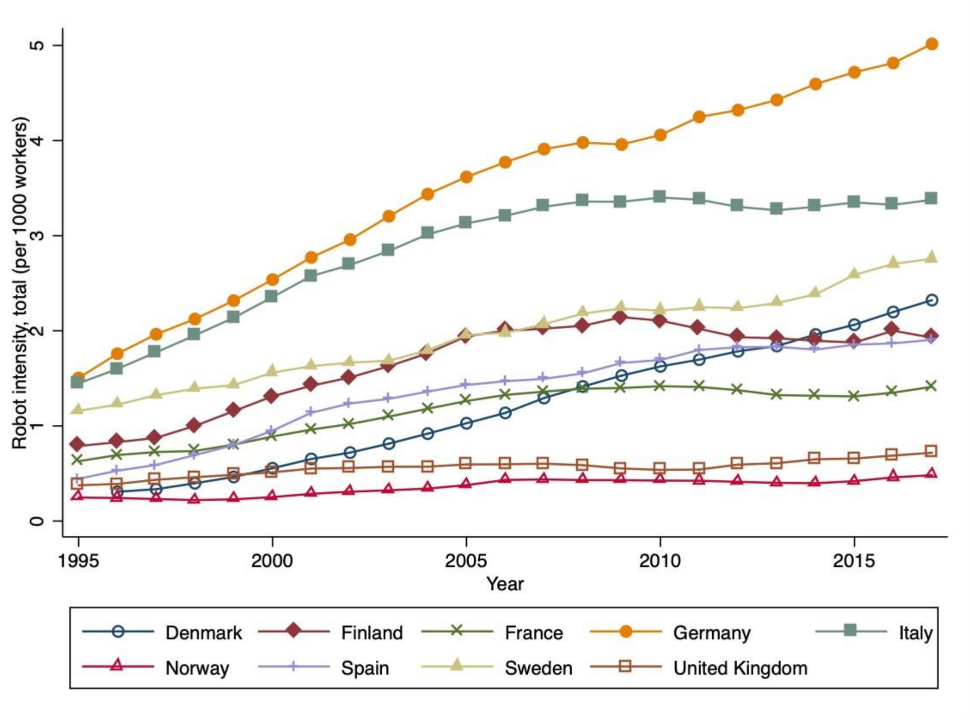
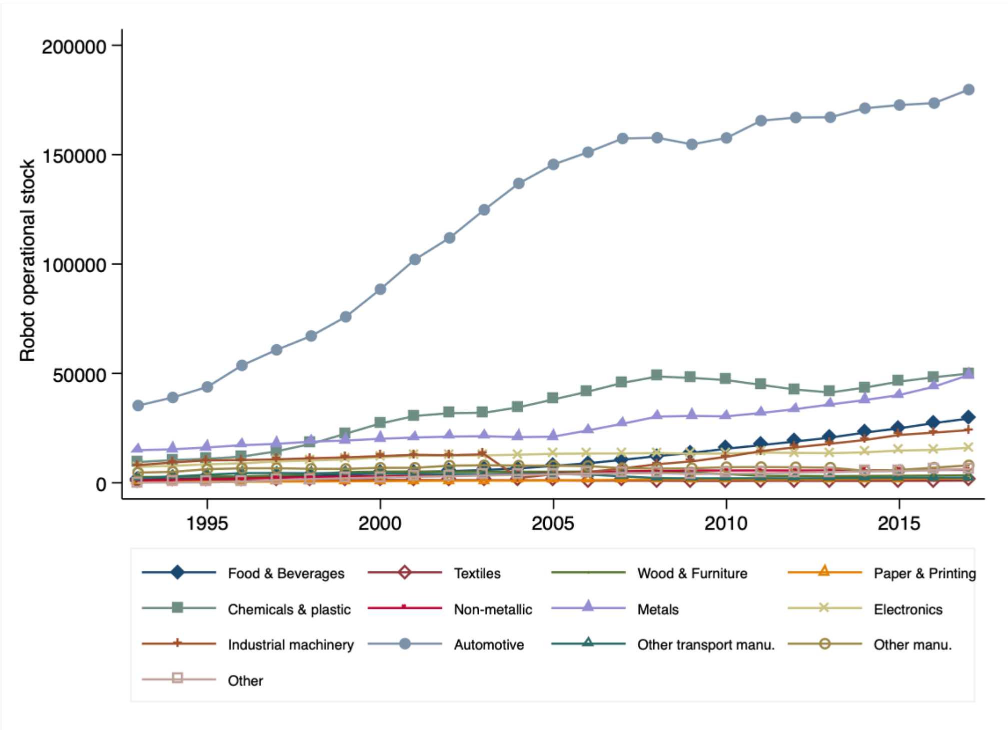
Figure 1 Industrial robot adoption in Europe

Panel A. Robot intensity by country



Panel B. Operational robot stock by industry



Sources: IFR, EUKLEMS and Statistics Norway
Notes: Panel A shows the change in robot intensity of production (the operational stock of industrial robots per 1000 workers) between 1993 and 2016 for nine European countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden and United Kingdom. Panel B presents the change in the operational stock of industrial robots at the industry level for nine European countries.

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Equation 1

$$APR^{c}_{i,(t_0,t_1)} = \frac{R^{c}_{i,t_1} - R^{c}_{i,t_0}}{L^{c}_{i,1990}} - \frac{R^{c}_{i,t_0}}{L^{c}_{i,1990}} g^{c}_{i,(t_0,t_1)}$$

where $R^{c}_{i,t}$ is the number of robots in industry *i* in country *c* at time *t*, $g^{c}_{i,(t_0,t_1)}$ is the growth rate of real gross output (2007=100) of industry in industry *i* in country *c* between t_0 and t_1, and $L^{c}_{i,1990}$ is the baseline employee level (per thousand workers) in industry *i* in country *c*. $\frac{R^{c}_{i,t_0}}{L^{c}_{i,1990}} g^{c}_{i,(t_0,t_1)}$ is the adjusted term to account for the robot adoption which could be driven by the expanding product demand in each industry *i*.

Ideally, we want to construct the measure of the robot penetration which only captures the exogenous technology improvement. However, robot adoption may well be affected by local industry-specific demand shocks. To address the issue of this endogenous bias, we use the average increase in the operational robots in the same set of industries in seven other European countries as an instrument to exploit the variation coming from the world technological frontier, which should not be correlated with shocks to local demand. We construct this average adjusted penetration of robots as follows:[4]

Equation 2

$$\overline{APR}_{i,(t_0,t_1)} = \frac{1}{7} \sum_{j \in J, j \notin c, DE} \left[\frac{R^{j}_{i,t_1} - R^{j}_{i,t_0}}{L^{j}_{i,1990}} - \frac{R^{j}_{i,t_0}}{L^{j}_{i,1990}} g^{j}_{i,(t_0,t_1)} \right]$$

where $R^{j}_{i,t}$ is the number of robots in industry *i* in country *j* at time *t*, $g^{j}_{i,(t_0,t_1)}$ is the growth rate of real gross output (2007=100) of industry in industry *i* in country *j* between t_0 and t_1, and $L^{j}_{i,1990}$ is the baseline employee level (per thousand workers) in industry *i* in country *j*. As

[4] Note that Germany is excluded from other European countries. As shown in Figure 1, its robot usage is far ahead of other countries so that the robot adoption trends could be less relevant for other countries. For Germany, we construct the adjusted penetration using Denmark, Finland, France, Italy, Spain, Sweden and United Kingdom. We also construct another measure by using Denmark, Finland, France, Italy and Sweden, which are used to construct the APR measure in Acemoglu and Restrepo (2020), for Germany, Norway, Spain and United Kingdom. For the rest of the countries, we replace the home country with the United Kingdom. These two APR variables are highly correlated, and the industry-level results are qualitatively similar, underlining the robustness of our APR measure.

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we would expect, Figure 2 shows that our two APR measures, with or without the automotive industry, are highly correlated. In the automotive industry, for example, the APR indicates that the adjusted increase of industrial robots per thousand workers is between 1 to 4 across all nine European countries. Turning to the relationship between our APR measure and employment, Figure 3 highlights the negative relationship between our adjusted penetration of robots and employment growth across industries. We note that industries that installed more industrial robots typically saw a reduction in employment.

2.2 Exposure to robots

Since we cannot observe the actual robot usage in a local labour market, we use a shift-share design to apportion each industry's robot penetration derived from equation 1 and 2 across local labour markets based on their industrial employment shares, following Acemoglu and Restrepo (2020). To capture local labour markets, we use units that roughly correspond to NUTS 3 or a more granular level. Our analysis ends in 2007 to avoid the potentially confounding effects of the Great Recession and later uncertainty surrounding Brexit. Local industry employment data are collected at the ISIC 3-digit level from the relevant national statistics offices or the Integrated Public Use Microdata Series International (IPUMS-International, Minnesota Population Center, 2020).[5]

To elucidate the impact of robots on jobs, we take advantage of the fact that there is substantial geographic variation in industry specialization. This means that local economies that have specialized in industries where more industrial robots are installed should be differentially affected by the robot revolution within a country. Our exposure to robots variable, thus, measures the predicted instead of actual change in the number of robots in each local labour market, and is written as:

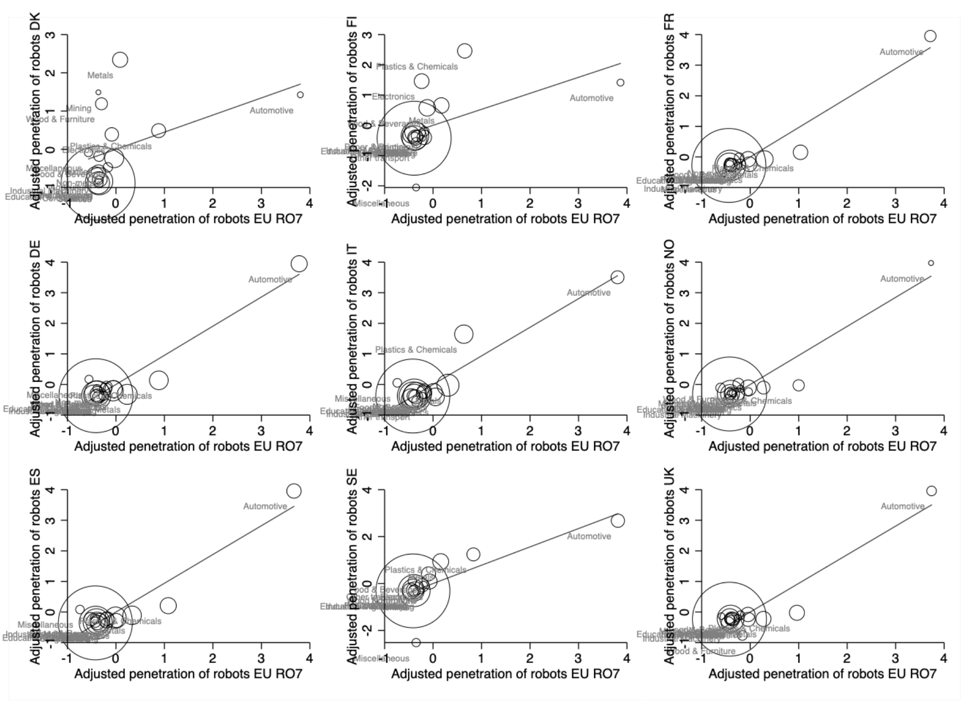
Equation 3

$$ER^{c}_{d,(t_0,t_1)} = \sum_{i \in I} l^{t_0}_{di} \cdot APR^{c}_{i,(t_0,t_1)}$$

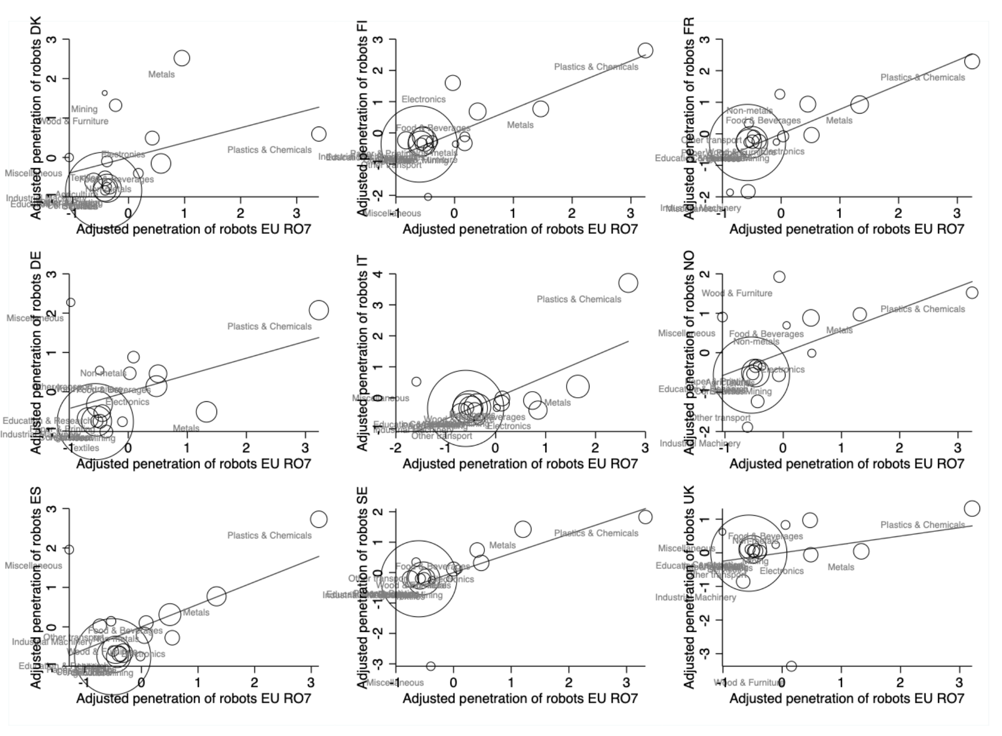
[5] We collect Census data for France and Spain from IPUMS-International. They are produced originally by the National Institute of Statistics and Economic Studies in France and the National Institute of Statistics in Spain.

Figure 2 Adjusted robot penetration in European countries

Panel A. All industries



Panel B. All industries, excluding automotive



Sources: IFR, EUKLEMS and Statistics Norway
Notes: Panel A shows the relationship between the home country's APR in equation 1 and the average European countries APR in equation 2 between 1993 and 2007 for 18 industries. Panel B presents the same plot excluding automotive industry. Marker size indicates industrial employment in the start-of-period.

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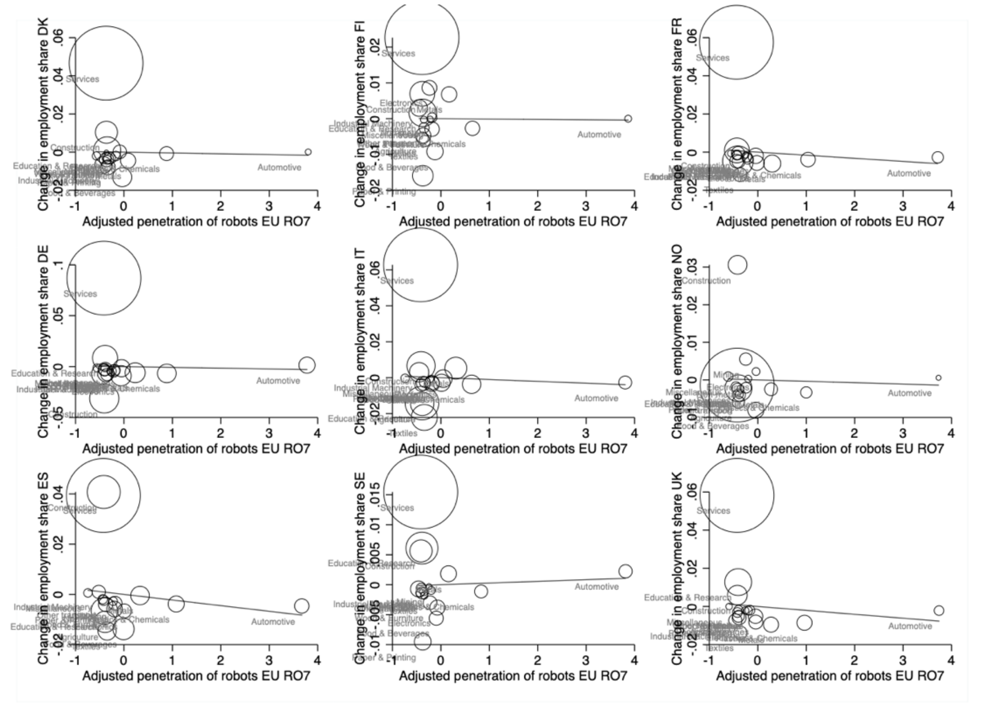
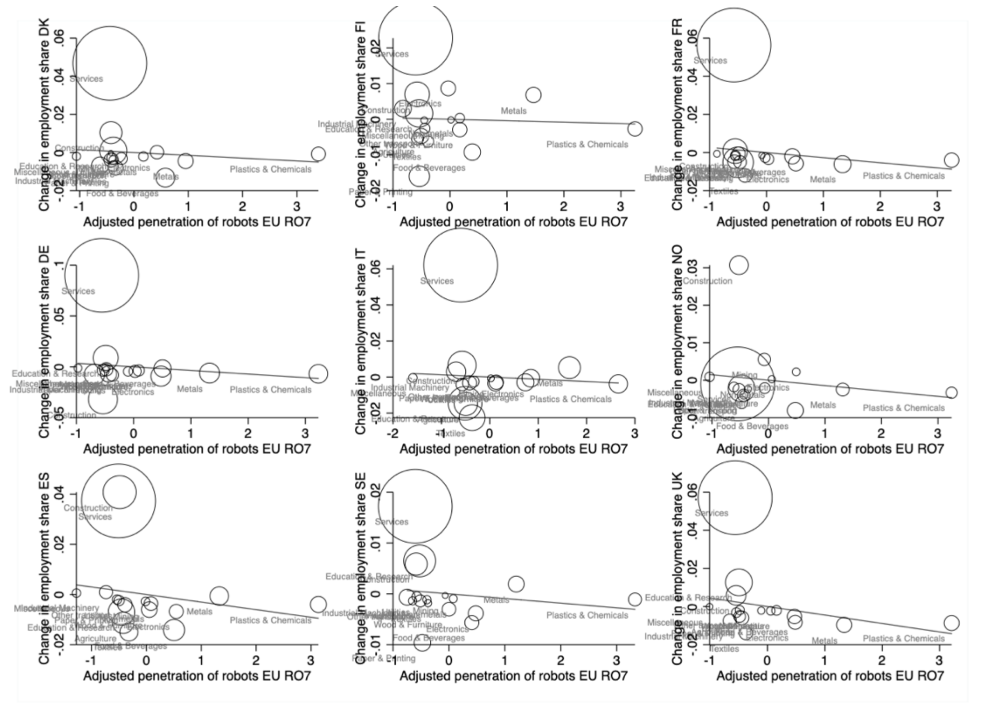
Figure 3 The relationship between industrial robots and employment

Panel A. All industries



Panel B. All industries, excluding automotive



Sources: IFR, EUKLEMS and Statistics Norway
Notes: Panel A shows the relationship between employment growth and average European countries APR defined in equation 2 during the period between 1993 and 2007 for 18 industries. Panel B presents the same plot excluding automotive industry. Marker size indicates industrial employment in the start-of-period.

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where $l_{di}^{t_0}$ is the share of industry *i* in total employment of local labour market *d* in the start-of-period t_0, and where $APR_{i,(t_0,t_1)}^{c}$ is as defined in equation 1. For each local labour market *d*, we assume the robot adoption rate in each industry is uniform. In appendix, we report the summary statistics of exposure to robots. In the average local labour market, the predicted change in operational robots per thousand workers is around 2.2 in Spain and Italy, while it is about 0.3 in Norway and United Kingdom. In other words, there is substantial variation in the exposure to robots across local labour markets, which could affect local employment differentially.

Beside the unobserved industrial demand shock discussed above, there is another concern of our identification strategy: that shocks to local labour demand, such as a local recession or changing tax incentives, are affecting the adoption of robot technology. To account for this, we take the employment shares from the previous decade which capture the historical industrial specialization before industrial robots were in use in the local market. The IV exposure measure is defined as in equation 4, exploiting the variation in industry-level adoption of robots in other European countries as well as historical industrial specialization across local labour markets:

Equation 4

$$ER_{d,(t_0,t_1)}^{IV} = \sum_{i \in I} l_{di}^{t_{-1}} \cdot \overline{APR}_{i,(t_0,t_1)}$$

where $\overline{APR}_{i,(t_0,t_1)}$ is derived from equation 2 and $l_{di}^{t_{-1}}$ allows us to mitigate any mechanical correlation or mean reversion associated with changes in industry employment that are the result of the anticipation of the introduction of industrial robots in the late 1980s.[6]

[6] Due to data constraints, we use the earliest year available. For Denmark, France and Norway, there are no industrial employment data available before 1990, and hence we use the local industrial employment shares in t_0.

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2.3 Exposure to Chinese imports

Our main trade data source is the widely used UN Comtrade database, which provides import and export data at the six-digit Harmonized System (HS) level across geographies and years. Due to lags in adopting the HS classification, trade data between nine European countries and China are only available from 1993 onward, and hence this is the first year used in our analysis.[7] We begin by mapping the commodities in the UN Comtrade database to three-digit SIC industries, using the HS1992-SIC crosswalk provided by Autor *et al*. (2013). Thereafter, we aggregate the SIC manufacturing industries to their 12 IFR manufacturing counterparts to have a measure that is comparable to our robot exposure variable.

Figure 4 shows the import penetration ratio across the countries in our sample between 1995 and 2017. In the 1990s, the Chinese import penetration ratio is below one for all countries. After China joined World Trade Organization (WTO) in 2001, the share increased rapidly, reaching more than 2 in most countries in 2007. In other words, all countries have experienced rising import competition from China over the past two decades.

Following Autor *et al*. (2013), our main measure of exposure to Chinese import competition is the change in per thousand US dollar Chinese imports per worker in a local labour market, where imports are apportioned to its share of national industry employment as follows:

Equation 5

$$ECI_{d,(t_0,t_1)}^{China-c} = \sum_{i \in I} \frac{L_{idt_0}^{c}}{L_{it_0}^{c}} \frac{M_{i,(t_0,t_1)}^{China-c}}{L_{dt_0}^{c}}$$

where $M_{i,(t_0,t_1)}^{China-c}$ is the observed change in imports from China per thousand US dollars (2007=100) in industry *i* between the start t_0 and end of period t_1, $L_{dt_0}^{c}$ is total employees in local labour market *d* at t_0 and $\frac{L_{idt_0}^{c}}{L_{it_0}^{c}}$ is local labour market d's share of national employees of industry *i*.

As there are concerns that local employment and imports from China may be positively correlated with unobserved shocks to product demand, we employ an instrumental variable strategy that accounts for the potential endogeneity of the exposure to Chinese imports.

[7] The earliest year for France and Italy is 1994.

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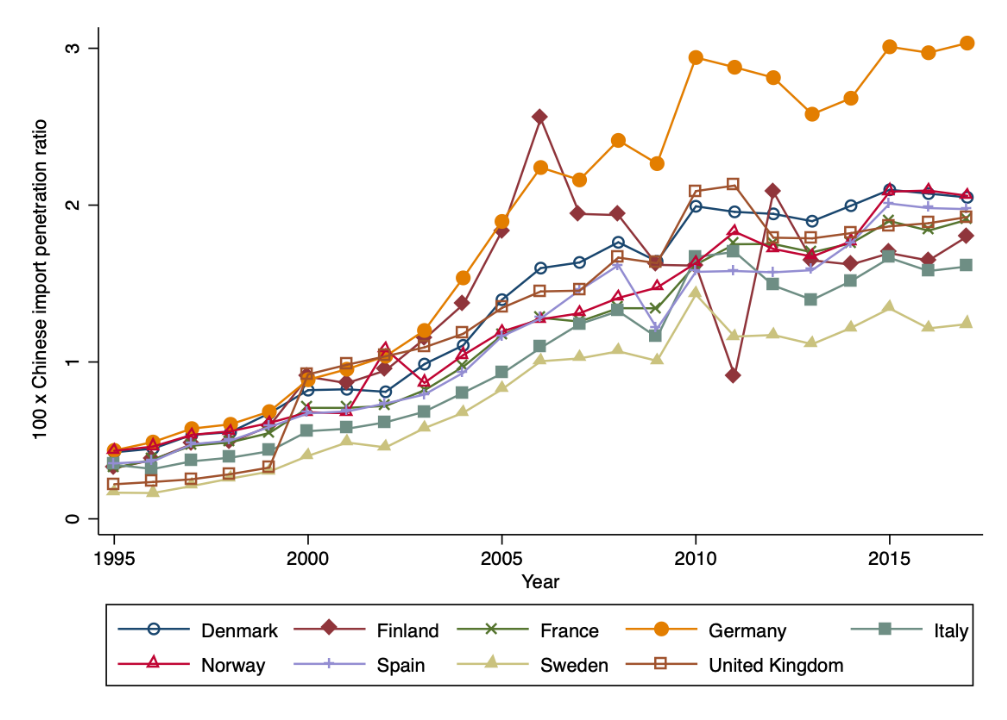
Figure 4 Growth of Chinese imports



Sources: UN Comtrade, World Bank
Notes: This figure plots the change in the import penetration ratio between 1995 and 2017 for nine European countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Swedena and United Kingdom. The import penetration ratios are defined as the ratio between the value of imports as a percentage of total domestic demand.

Consistent with the empirical strategy employed by Autor *et al*. (2013) to identify the supply-driven component of imports from China, we instrument for the growth in Chinese imports to each country by using the historical industry composition and growth of Chinese imports in four other high-income countries, which have comparable trade data covering the full sample period. These countries are: Australia, Japan, New Zealand, and Switzerland. The instrumental variable is defined as:

Equation 6

$$ECI^{China-HI}_{d,(t_0,t_1)} = \sum_{i \in I} \frac{L^c_{idt_{-1}}}{L^c_{it_{-1}}} \frac{M^{China-HI}_{i,(t_0,t_1)}}{L^c_{dt_{-1}}}$$

where $M^{China-HI}_{i,(t_0,t_1)}$ is the observed change in the sum of other countries imports per thousand US dollars (2007=100) from China in industry i between the start t_0 and end of period t_1. We also replace the start-of-period employment level by industry and local labour market with

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those from the prior decade. This is to mitigate potential simultaneity bias, which may be the result from anticipated trade growth.[8] Figure 5 Panel A shows that the two measures of exposure to Chinese imports, in the countries in our sample and other high-income countries, are highly correlated. Electronics and Textiles are the main industries exposed more to import competition from China. Unlike the previously observed negative relationship between our adjusted penetration of robots measure and industrial employment growth (Figure 3), we do not observe a similar negative correlation between import competition from China and employment growth across industries in Panel B. This suggests that the impact of Chinese import competition on local employment might have been less pervasive in Europe. This contrasts previous findings for the United States (Autor *et al*., 2013).

2.4 Descriptive statistics

We collect data from national statistics offices and the IPUMS-International to construct our long difference specifications for the period between the early 1990s and 2007 at NUTS 3 or a more granular level. An exception is France, where we use 22 NUTS 2 level units due to limited data availability. To be comparable to existing literature (Acemoglu and Restrepo 2020; Dauth *et al*. 207; Dottori 2020), the main outcome variable is the employment-to-population ratio, including all employed persons/employees across all sectors. Table 1 provides data coverage of each country and Appendix A documents the data collection in more detail.

As controls, we include a set of demographic variables, including the log of population, the male population share, the foreign born population share as well as ethnic population share. We also include the share of population above 65 and the share of the population with a higher education.[9] As the pre-existing industrial structure could have confounding effects on local labour markets, we further include a set of local level industry variables to ensure that

[8] The same data constraints apply when constructing the APR measure.

[9] We define higher education as at least one year of college and above for Denmark, Finland, France, Spain and Sweden. For Italy, it refers to those with diploma and above. For the United Kingdom, it indicates those with qualifications. For Germany, we use the share with a university degree. Because of these differences in educational systems and data availability, our estimates of the impact of robots on different skill groups across countries need to be interpreted with care.

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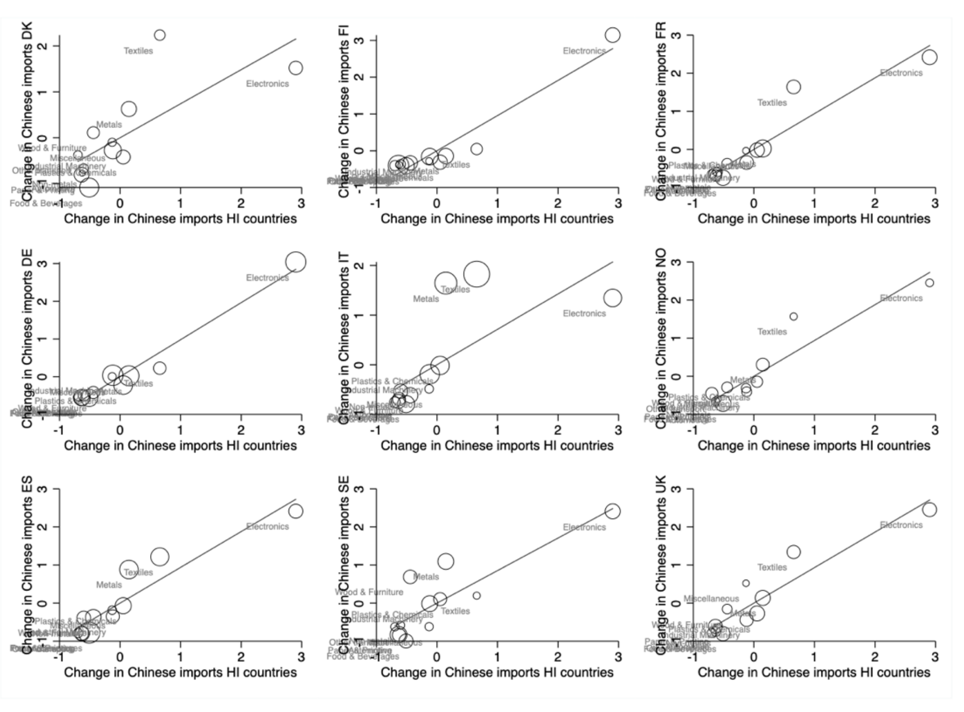
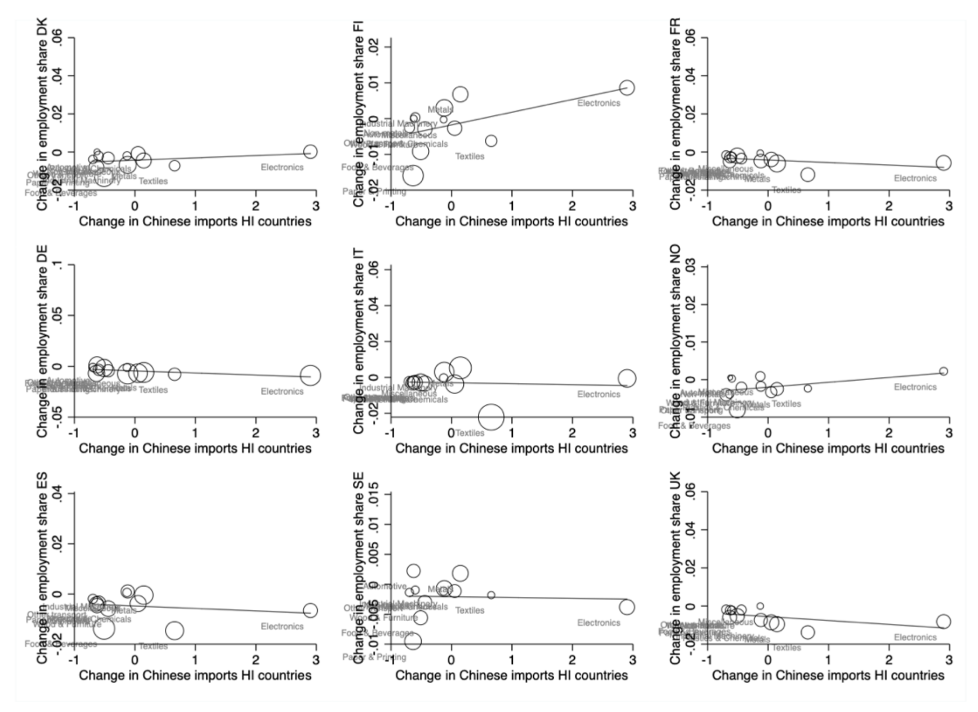
Figure 5 Chinese import competition in Europe

Panel A. Change in Chinese imports, 1993-2007



Panel B. Change in employment share vs. change in Chinese imports



Sources: UN Comtrade, EUKLEMS and Statistics Norway

Notes Panel A plots the relationship between the differences in Chinese imports of the home country and the aggregate differences in Chinese imports of four high-income countries between 1993 and 2007 for 12 manufacturing industries. Panel B shows the relationship between employment growth and aggregate differences in Chinese imports of four high-income countries between 1993 and 2007 for 12 manufacturing industries. Marker size indicates industrial employment in the start-of-period.

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Table 1 Country profiles

Country	Number of observations	Long Differences	Spatial Unit	Data sources
Denmark	99	1994-2007	Municipality 2007	Denmark Statistics
Finland	70	1993-2007	Sub-region	Finland Statistics
France	22	1990-2006	NUTS2	IPUMS-International
Germany	402	1995-2007	District	German Federal Statistical Office, Institute for Employment Research (IAB)
Italy	110	1991-2011	Province 2009	National Institute of Statistics (Istat)
Norway	74	1995-2007	Economic region	Norway Statistics
Spain	50	1991-2011	Province	IPUMS-International
Sweden	100	1993-2007	Local labour markets 1998	Sweden Statistics
United Kingdom	352	1991-2007	Local authority district, prior to 2015	NOMIS, provided by Office for National Statistics

exposure variables do not work as proxies for other trends accounting for the change in employment. For example, both robots and Chinese import competition have proportionally large impacts on light manufacturing industries which are relatively easy to outsource or automate.[10] Other industry variables include the share of employment in mining and construction, and the share of female workers in manufacturing.

Table 2 provides some descriptive statistics indicating how local labour markets with high and low exposure to robots have different labour market characteristics. The tables with complete summary statistics can be found in Appendix A.[11] Column 1 shows the mean for all local labour markets, while columns 2 to 5 present the mean outcomes and exposure to Chinese imports by quartiles of exposure to robots. In column 2 to 5, there are parallel trends between exposure to robots and Chinese imports across four quartiles, implying the exposure to Chinese imports could be the confounding factor. Generally, the labour markets that were more exposed to both robots and Chinese imports experienced more negative labour market trends. We next turn to disentangling the impacts of trade and technology on local labour markets in Europe.

[10] Foods, textiles and paper and printing are classified as light manufacturing.

[11] Also, in terms of the control variables used in the main specifications, we note that, for most countries, the share of light manufacturing employment, the share of female employment in manufacturing show economically significant differences between high- and low-exposure local labour markets.

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Table 2 Summary Statistics

	Variables	Means by quartiles of exposure to robots, IV				
		All LMs (1)	First quartile (2)	Second quartile (3)	Third quartile (4)	Fourth quartile (5)
Denmark	Exposure to Chinese imports, IV	48.185	28.793	52.192	59.617	60.764
	Change employment to population ratio	3.869	3.725	4.083	4.134	3.683
Finland	Exposure to Chinese imports, IV	54.390	28.590	47.593	62.933	70.920
	Change employment to population ratio	7.122	5.316	7.644	7.435	6.504
France	Exposure to Chinese imports, IV	6.025	4.944	5.614	7.300	6.981
	Change employment to population ratio	1.987	1.321	2.871	1.774	2.878
Italy	Exposure to Chinese imports, IV	9.984	5.701	7.608	10.942	13.672
	Change employment to population ratio	1.403	2.746	1.768	0.679	0.775
Norway	Exposure to Chinese imports, IV	64.553	42.439	51.373	73.746	100.384
	Change employment to population ratio	12.043	12.800	13.821	11.279	10.397
Spain	Exposure to Chinese imports, IV	17.007	6.840	10.481	13.182	26.021
	Change employment to population ratio	4.053	3.908	2.955	3.329	4.960
Sweden	Exposure to Chinese imports, IV	29.846	18.377	2.686	33.932	32.761
	Change employment to population ratio	4.956	4.735	4.657	4.989	5.717
United Kingdom	Exposure to Chinese imports, IV	6.381	4.155	9.097	7.265	8.074
	Change employment to population ratio	2.172	2.181	2.063	3.235	1.444

Notes: Columns 1 shows the sample means for all local labour markets. Column 2-5 present means by quartiles of exposure to robots from equation 4. The means are weighted by population in the start-of-period.

3. Empirical Strategy

In this section, we present our reduced-form regressions and IV results, estimating the impact of robots and Chinese imports on jobs across local labour markets.

3.1 Exposure to robots and Chinese imports

Equation 7 below is our reduced-form ordinary least squares (OLS) specification to estimate the impacts of robots and trade on local labour markets over the period t_0 to t_1:

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Equation 7

$$Y^c_{d,(t_0,t_1)} = \alpha + \beta_1\, ER^c_{d,(t_0,t_1)} + \beta_2\, ECI^{China-c}_{d,(t_0,t_1)} + X_{dt_0} B_3 + \delta_r + e_d$$

where the outcome variable $Y^c_{d,(t_0,t_1)}$ is the change in the employment-to-population ratio between t_0 and t_1 in local labour market d, located in region r in country c. The main variables of interest are $ER^c_{d,(t_0,t_1)}$ and $ECI^{China-c}_{d,(t_0,t_1)}$, which correspond to the exposure to robots and Chinese imports as defined in equation 3 and 5, respectively. Also included are a regional dummy, δ_r, that allow for differential employment trends across regions, and a vector of control variables, X_{dt_0}, measuring the start-of-period demographic and industry structure in each local labour market. The identifying assumption is that the labour markets where industries have kept up with significant improvements in advanced robotics are not experiencing other shocks or trends.

Table 3 presents our results from estimating equation 7 with a long-differences OLS specification, where we regress the change in the employment-to-population ratio on the exposure to robots in Panel A and both the exposure to robots and Chinese imports in Panel B.[12] Our baseline specifications are weighted by population in the start-of-period to account for the variation in market size as well as reported standard errors that are robust clustered by regions above the local labour market level. We drop singleton groups in regressions where fixed effects are nested within clusters. This helps to prevent overstating statistical significance and causing incorrect inference when using cluster-robust standard errors in OLS or 2SLS. Also, we reckon that the estimates for France could be imprecise as there are only 22 observations at the NUTS 2 level, even when only including two main demographic characteristics (the share of population over 65 and with high education) as well as three industrial ones: the employment shares of light-manufacturing, mining and construction.

In column 1-9, in addition to regional fixed effects, we control for the full set of demographic and industrial characteristics, described in section 2.4, in the start-of-period. Since our regression specifications are in changes, these controls allow for differential trends by these local labour market characteristics. In Panel A, although the impact of exposure to robots on the employment-to-population ratio is negative except in Spain, it is not estimated

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[12] To match the time window over which we measure the adjusted penetration of robots, we rescale the outcomes to the equivalent period. For example, for UK's outcome variable, we define long differences as (y_{2007}-y_{2001}) + 0.8 x (y_{2001}-y_{1991}).

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Table 3 The effects of robots and Chinese imports on employment

	Long Difference								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Denmark	Finland	France	Germany	Italy	Norway	Spain	Sweden	UK
	Panel A. Exposure to robots, OLS								
Exposure to robots	-0.001	0.057	-0.477	-0.038	-0.332**	-0.963	0.052	-0.755*	-0.323
	(0.792)	(0.492)	(0.405)	(0.043)	(0.122)	(0.994)	(0.075)	(0.430)	(0.492)
	Panel B. Exposure to robots and Chinese imports, OLS								
Exposure to robots	0.564	-0.641	-0.713	-0.037	-0.306*	-0.525	0.042	-0.736*	-0.333
	(0.968)	(0.400)	(0.729)	(0.045)	(0.150)	(1.081)	(0.072)	(0.407)	(0.479)
Exposure to Chinese imports	-0.432	0.345***	0.875	-0.105**	-0.277	-0.650	0.309	0.953	-0.482**
	(0.518)	(0.098)	(1.946)	(0.043)	(0.602)	(0.640)	(0.250)	(0.765)	(0.211)
Observations	99	70	20	357	110	74	49	100	352
	Panel C. Exposure to robots, 2SLS								
Exposure to robots	0.922	0.329	-0.501	-0.075	-0.395***	-3.390**	0.061	-0.600	-1.259**
	(0.987)	(0.436)	(0.414)	(0.045)	(0.127)	(1.308)	(0.086)	(0.545)	(0.562)
	Panel D. Exposure to robots and Chinese imports, 2SLS								
Exposure to robots	1.064	0.068	-0.295	-0.076	-0.422***	-3.220*	0.030	-0.586	-0.937*
	(1.262)	(0.527)	(0.567)	(0.046)	(0.138)	(1.529)	(0.075)	(0.512)	(0.529)
Exposure to Chinese imports	-0.282	0.243	0.196	-0.166***	0.280	-0.203	0.326	0.132	-0.816***
	(0.850)	(0.152)	(1.892)	(0.054)	(0.857)	(0.682)	(0.271)	(1.374)	(0.313)
Cragg-Donald Wald F statistic	26.90	23.17	1.85	434.54	140.07	48.22	470.31	37.25	140.76
Observations	99	70	19	319	110	74	49	100	352
Regional FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents estimates of the impact of the exposure to robots and Chinese import competition. The outcome variables are the long-difference in the total employment-to-population ratio. Regressions are weighted by population in the start-of-period. The covariates and regional effects included in each model are indicated in the bottom rows. The list of covariates is documented in Appendix A. The missing geographic values in Germany are due to confidentiality-related data limitations. Statistical significance based on clustered standard errors (reported in parentheses) is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

precisely across countries. For Italy and Sweden, there is a strong negative relationship between exposure to robots and employment changes in local labour markets with a coefficient of -0.33 (standard error = 0.12) and -0.76 (standard error = 0.43), respectively.

In Panel B, we examine if exposure to trade has additional effects on local employment. Our estimates of the impact of robots remain significant and negative in Italy and Sweden after controlling for trade exposure to China. Figure 6 provides a residual regression plot showing the variation of the exposure to robots. The solid line shows the regression relationship conditional on covariates as in Panel B of Table 3, while the dashed line presents the same regression excluding the top one percent of local labour markets with highest

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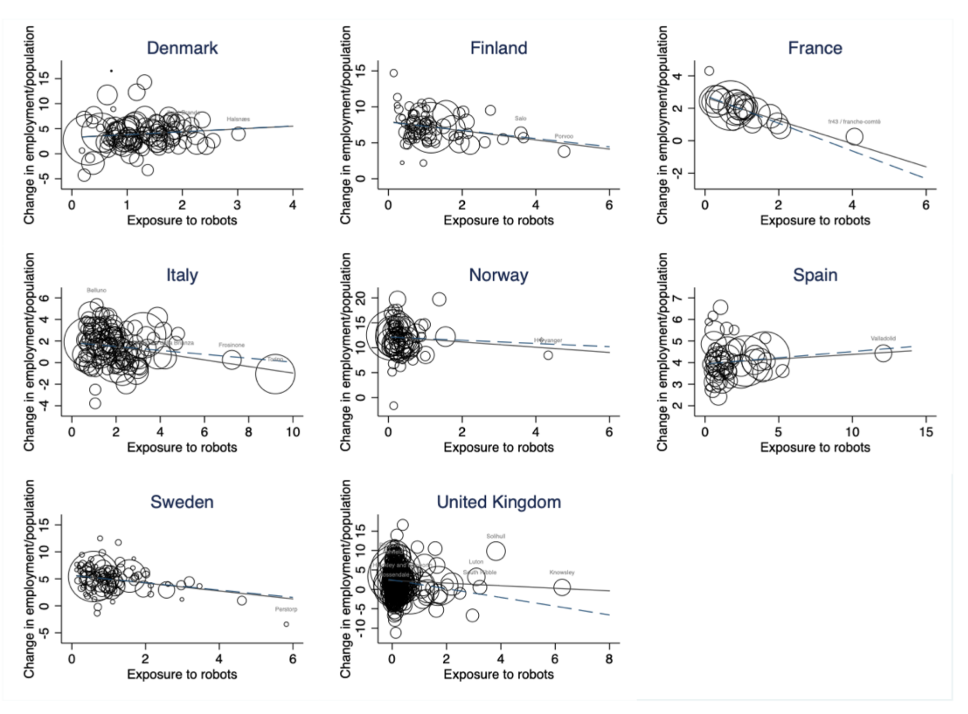
Figure 6 Charting the impact of robots on employment



Notes: The figure presents the regression residual plot of robot exposure in panel B of Table 3. The solid line corresponds to a regression with the local labour market population in the start-of-period as weights. The dashed line is for a regression which in addition excludes the top one percent of local labour markets with the highest exposure to robots or Chinese imports. Marker size indicates the loc al labour markets population in the start-of-period.

exposure to robots or Chinese imports. The size of each circle indicates the local market's population in the start-of-period, and we can observe substantial variation in industrial composition across local labour markets within each country. The distribution of exposure to robots is mainly skewed to the right with only a handful local labour markets with large values. Notably, many of them are specialized in automotive industry, such as Turin in Italy, Valladold in Spain, Olofström in Sweden and Solihull in United Kingdom, or the plastic and chemical industry, such as Porvoo in Finland and Perstorp in Sweden. These highly specialized markets also reflect the industry-level variation in robots penetration in Figure 2. Hence, Figure 6 depicts countries with relatively many local labour markets exposed to robots, like Italy, Sweden or United Kingdom, which faced larger displacement effect than others, such as Denmark or Spain.

As pointed out by Acemoglu and Restrepo (2020), the identifying assumptions behind these exposures are that a local labour market with higher exposure to robots or trade is not experiencing differential labour market trends for other reasons and that the baseline industry share in the start-of-period is exogenous. However, other domestic industry-specific demand shocks can affect robot installation across local labour markets. To address this

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endogeneity concern, we estimate equation 8 using two-stage least squares (2SLS) with our exposure to robots variable instrumented by a local labour markets historical industry structure as well as average adjusted penetration of robots of the other seven European countries with advanced robotic technology, $ER^{IV}_{d,(t_0,t_1)}$ derived from equation 4, and the Chinese imports variable instrumented by contemporaneous changes in imports from China in the other four high-income countries: Australia, Japan, New Zealand and Switzerland, $ECI^{China-HI}_{d,(t_0,t_1)}$ derived from equation 6. The 2SLS specificaiton also includes a set of start-of-period covariates and regional fixed effects as in equation 7:

Equation 8

$$Y^{IV}_{d,(t_0,t_1)} = \alpha + \beta_1\, ER^{IV}_{d,(t_0,t_1)} + \beta_2\, ECI^{China-HI}_{d,(t_0,t_1)} + X_{d t_0} B_3 + \delta_r + e_d$$

Figure 7 depicts our first-stage relationship in the form of residual plots, presenting each country's exposure to robots and Chinese imports at the local labour market level against our IV variables, respectively. It shows that there is a high correlation between the usage of robots by other European industries and those in our sample (Panel A). It also shows a strong relationship between Chinese import competition in the investigated countries and Chinese imports in other high-income countries (Panel B).

Panel C and D in Table 3 present our IV estimates for the long-differences specifications analogous to those in Panel A and B. It also reports the Cragg-Donald Wald F statistic. As we have two endogenous regressors, the F statistic suggests that the specifications are not weakly identified for most countries except France, which is probably due to the small sample size. The IV estimates quantify the impact of one additional robot per thousand workers on employment in a given local labour market relative to others. The estimate of exposure to robots in Italy in Panel D, for example, implies that the adoption of one additional robot per thousand workers in a location reduces its employment-to-population ratio by 0.42 percentage points relative to other areas. In all specifications, the results from our 2SLS estimates share a similar pattern as our OLS regressions but with larger coefficients. The larger magnitudes of our 2SLS coefficients are consistent with OLS regressions being contaminated by unobserved product or labour demand shocks, which induce positive covariation between industry employment and robot installation or trade, thereby leading the OLS estimates to understate the true impact of robots and Chinese imports on

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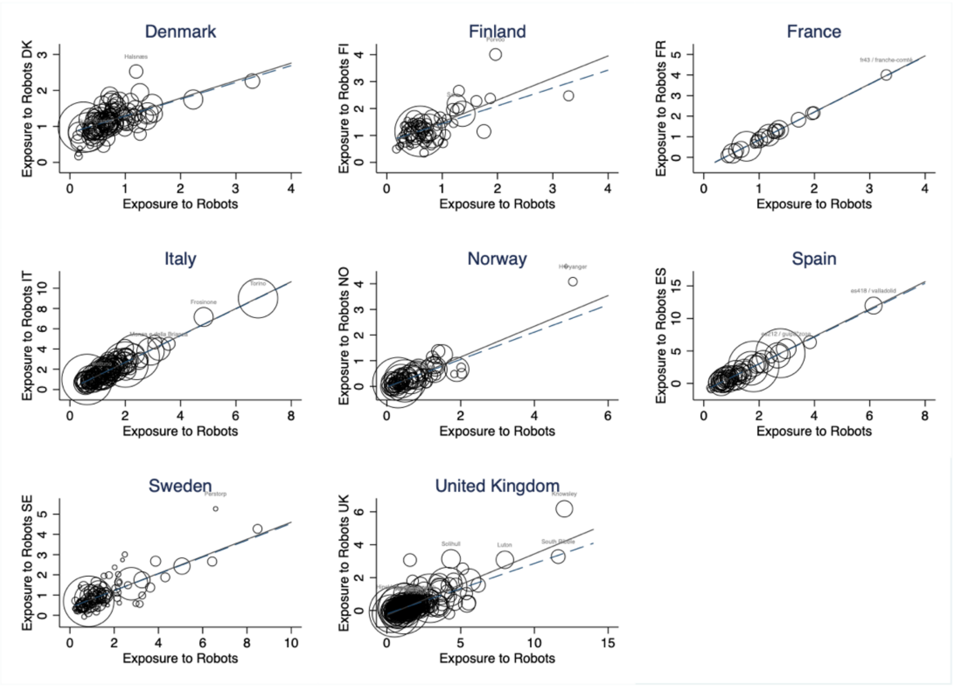
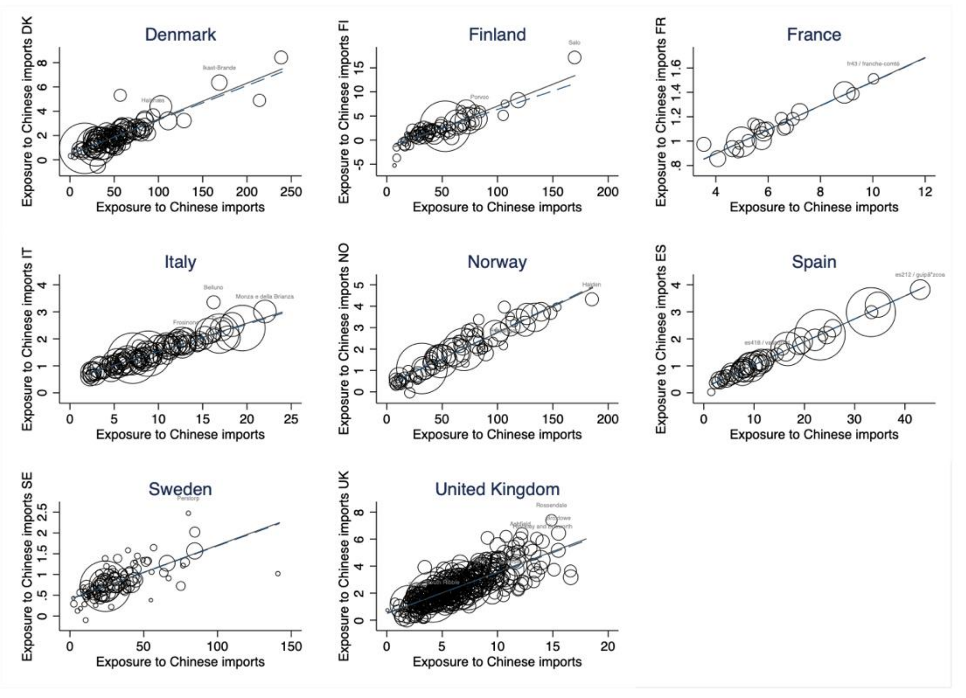
Figure 7 Chinese import competition in Europe

Panel A. Exposure to robots



Panel B. Exposure to Chinese imports



Notes: The figure presents the relationship between exposure to robots and Chinese imports (from the EU and other high-income countries) and a country's exposure to robots and Chinese imports for the period between 1990s and 2007, after the covariates in panel B of Table 3 have been partialled out. The solid line corresponds to a regression with the local labour markets population in the start-of-period as weights. The dashed line is for a regression which in addition excludes the top one percent of local labour markets with highest exposure to robots or Chinese imports. Marker size indicates the local labour markets population in the start-of-period.

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employment. The results indicates that the displacement effects of robot adoption are not dominant in Denmark, Finland and Spain, while strong negative impacts are shown in Italy, Norway and the United Kingdom.[13]

In Norway, where the impact of robots is by far most significant economically, our baseline estimate implies that one additional robot per thousand workers in a given local labour market reduced its employment-to-population ratio by 3.22 percentage points. It must be remembered that these estimates also capture indirect employment effects outside the manufacturing sector. Nonetheless, the impact of robots on local labour markets in Norway is dramatically larger than observed in the United States and other EU countries.[14] This is probably due to the fact that the robot intensity of production in Norway is the lowest among the nine countries in our sample. This would imply that robot adoption is subject to diminishing returns in production, consistent with the findings of Graetz and Michaels (2018), showing that the productivity effect of one additional robot declines as the robot stock expands. It is of course true that a higher productivity effect would help offset the displacement effect, at least in part (Acemoglu and Restrepo, 2018). Nonetheless, while the displacement effect is concentrated locally, the productivity effect is much more dispersed and is thus not fully captured in our local employment estimates.

3.2 Composition effects

Table 4 presents the estimated impact of robots and Chinese imports on the employment-to-population ratio in manufacturing (Panel A) as well as outside manufacturing (Panel B). In the manufacturing sector, we find that robots reduced employment in all countries in our sample, but the effect is only statistically significant in Italy, Spain, and the United Kingdom. The impact of Chinese imports, in contrast, is not consistently negative, but also not statistically significant in most countries. For example, we find that Chinese imports reduced employment in Italy, Spain, and the United Kingdom, but seemingly boosted manufacturing employment in Finland.

[13] We note that our findings for France naturally differ from those of Acemoglu and Restrepo (2020), who examine the impact of robots on employment on the firm-level. In contrast, we focus on the employment impact of robots across local labour markets.

[14] For example, Acemoglu and Restrepo (2020) estimate that one robot replaces 6 workers locally in the US. Dauth *et al.* (2017) found that one robot replaces 2 manufacturing workers in Germany.

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Table 4 The effects of robots and Chinese imports on manufacturing and non-manufacturing employment

	Long Difference, 2SLS								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Denmark	Finland	France	Germany	Italy	Norway	Spain	Sweden	UK
	Panel A. Manufacturing employment								
Exposure to robots	-0.244	-0.291	-0.357	-0.042	-0.210***	-0.838	-0.157***	-0.362	-0.599**
	(0.955)	(0.420)	(0.318)	(0.037)	(0.067)	(0.707)	(0.042)	(0.365)	(0.246)
Exposure to Chinese imports	-0.592	0.287**	-0.146	-0.027	-0.968**	0.167	-0.889***	0.794	-0.763***
	(0.334)	(0.102)	(1.054)	(0.034)	(0.458)	(0.213)	(0.146)	(1.221)	(0.132)
	Panel B. Non-manufacturing employment								
Exposure to robots	1.292	0.445	0.048	-0.035**	-0.212*	-2.325*	0.183*	-0.255	-0.310
	(1.218)	(0.310)	(0.518)	(0.017)	(0.121)	(1.303)	(0.088)	(0.316)	(0.450)
Exposure to Chinese imports	0.323	-0.058	0.542	-0.145***	1.248	-0.356	1.195***	-0.527	-0.130
	(0.840)	(0.110)	(1.527)	(0.037)	(1.095)	(0.586)	(0.376)	(0.823)	(0.269)
Observations	99	70	19	319	110	74	49	100	352
Regional FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents 2SLS estimates of the impact of the exposure to robots and Chinese import competition. The outcome variables are the long-difference in the manufacturing or non-manufacturing employment-to-population ratio. Regressions are weighted by population in the start-of-period. The covariates and regional effects included in each model are indicated in the bottom rows. The list of covariates is documented in Appendix A. The missing geographic values in Germany are due to confidentiality-related data limitations. Statistical significance based on clustered standard errors (reported in parentheses) is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

Outside the manufacturing sector, we also find that robots increased employment in Spain. This is consistent with a reallocation of employment from manufacturing to non-manufacturing industries due to employment spillovers. For instance, robotization in manufacturing industries might increase productivity and the demand for complementary services such as engineering consulting and marketing. This countervailing effect might explain why both exposure measures do not have an impact on the aggregate employment-to-population ratio presented in column 7 of Table 3. Conversely, robot exposure reduced the local demand for jobs outside the manufacturing sector in Germany, Italy and Norway. We note that our estimates differ from those of Dauth *et al*. (2017), who find that robotization increased employment outside the German manufacturing sector between 1994 and 2014. One possible explanation for this difference is that robots did more to offset the displacement effect in the post-recession period, which we do not consider due to the potential confounding effects from the recession itself. For example, Jungmittag and Pesole (2019)

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show that robots in Europe had a much smaller impact on aggregate labour productivity in the 1995-2007 period, relative to the period 2008-2015, when robots spread to more industries. This might also explain why Dottori (2020) finds no harmful impact of robots on total employment across Italy between the early 1990s and 2016. Reassuringly, however, for the period up until 2001, his estimates are similar to ours.

3.3 Effects by industry

As shown in Figure 1, the automotive industry adopted more robots than any other sector between 1993 and 2007. This raises the concern that our estimates may be confounded with other changes affecting this particular industry. To address this concern, in Table 5, we decompose our measure of exposure to robots into two variables. The first measures the penetration of robots in the automotive industry, while the other captures the use of robots across all other industries. The 2SLS estimates show that the effects of both robot adoption variables are generally negative. However, the employment impact of robots in the auto industry is less economically and statistically significant relative to industrial robots in other industries. These results are reassuring, not only because they indicate that the effects are not solely driven by the automotive industry, but also because they show that exposure to other industrial robots have a much stronger and persistent impacts on local labour markets across countries.

3.4 Impacts by demographic groups

We next turn to investigating if various groups in the labour market are impacted differentially by robots. Table 6 reports 2SLS long-differences specifications of the change in the employment-to-population caused by robots. Overall, we find that the impact on male employment is consistently negative across the countries in our sample, although imprecisely estimated (Panel A). This speaks to the fact that roughly 60 to 70 percent of the manufacturing workforce across the nine countries in our sample is male. The picture for female employment is more mixed and the impact is even significantly positive in the case of Denmark. We note that this is in line with our previous finding that robots increased employment outside the Danish manufacturing sector (see Table 4).

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Table 5 The role of the automotive industry

	Long Difference, 2SLS								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Denmark	Finland	France	Germany	Italy	Norway	Spain	Sweden	UK
Exposure to robots in automotive	-0.198	5.948	0.212	-0.050	-0.455**	0.096	0.060	-0.589	-0.612
	(1.843)	(4.307)	(0.879)	(0.038)	(0.172)	(1.091)	(0.065)	(0.518)	(0.452)
Exposure to robots in other industries	-1.078	-0.900**	-7.403	-0.872***	-0.928*	-12.833***	-1.414	-0.436	-15.975**
	(1.545)	(0.316)	(6.748)	(0.208)	(0.536)	(3.145)	(0.841)	(1.022)	(7.485)
Observations	99	70	19	319	110	74	49	100	352
Regional FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents 2SLS estimates of the impact of the exposure to robots and Chinese import competition. The outcome variables are the long-difference in the total employment-to-population ratio. Regressions are weighted by population in the start-of-period. The covariates and regional effects included in each model are indicated in the bottom rows. The list of covariates is documented in Appendix A. The missing geographic values in Germany are due to confidentiality-related data limitations. Statistical significance based on clustered standard errors (reported in parentheses) is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

In Panel B, we explore the impact of robots across different age groups. On balance, robots seem to reduce the employment prospects of primarily younger workers. While imprecisely estimated, robots have a consistently negative impact on employment for those aged 24 and younger, Italy being the exception. Instead, robots in Italy reduced employment among middle-aged workers (age 25-54).[15] Conversely, we find that robots increased employment among those aged 55 and above in some countries, notably in Finland and Germany. One possible explanation is that automation increases the demand for supervisors and managers in some settings.

Finally, in Panel C, we explore the effect of robots on different skill groups, where we follow other empirical studies (such as Acemoglu and Restrepo, 2020; Dauth *et al*., 2017; Autor *et al*., 2015) using education attainment as a proxy for worker's skill level. We define skilled workers as those with some college/university degree or above.[16] Doing so, we find no evidence suggesting that industrial robots directly complement skilled workers, unlike other

[15] We note that age groups are reported somewhat differently across countries. For Italy and the United Kingdom, the age groups are defined as age 29 and below, age 30-54, and age 55 and above.
[16] Since we lack a consistent indicator for qualifications between the 1991 and 2011 UK Census, we define skilled workers in the UK as those in professional/managerial and technical/skilled non-manual/skilled manual occupations, while unskilled workers are those in partly skilled/unskilled occupations. Thus, it must be noted that our definition of skill varies somewhat across countries.

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Table 6 The impact of robots on demographic groups

		Long Difference, 2SLS								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Denmark	Finland	France	Germany	Italy	Norway	Spain	Sweden	UK
		Panel A. Gender								
	Female	1.244**	-0.061	0.068	-0.023	0.030	-0.379	0.044	-0.251	-0.183
		(0.539)	(0.214)	(0.311)	(0.015)	(0.027)	(0.362)	(0.064)	(0.205)	(0.297)
	Male	-0.078	-0.386	-0.545	-0.026	-0.032*	-0.007	-0.014	-0.429	-0.388
		(0.728)	(0.267)	(0.398)	(0.034)	(0.017)	(0.405)	(0.053)	(0.258)	(0.301)
		Panel B. Age								
	Age 24 and below	-0.047	-0.072	-0.355	-0.023**	0.162***	-0.328	-0.037	-0.067	-0.043
		(0.231)	(0.085)	(0.460)	(0.009)	(0.033)	(0.205)	(0.031)	(0.131)	(0.178)
Exposure to robots	Age 25-54	1.215	-0.017	-0.148	-0.037	-0.260*	-0.149	0.052	-0.528*	0.395
		(0.725)	(0.291)	(0.635)	(0.033)	(0.141)	(0.763)	(0.044)	(0.300)	(0.455)
	Age 55 and above	0.209	0.646**	0.208	0.012*	0.041	-0.291	0.014	0.009	-0.060
		(0.233)	(0.260)	(0.275)	(0.006)	(0.046)	(0.216)	(0.023)	(0.144)	(0.145)
		Panel C. Skills								
	Unskilled	0.904	0.748	-0.069	-0.036***		-0.661	-0.127		-0.547***
		(0.584)	(0.562)	(0.721)	(0.013)		(1.585)	(0.087)		(0.128)
	Skilled	0.419	-0.200	-0.233	-0.012		-0.326	0.158***		-0.225
		(0.556)	(0.244)	(0.908)	(0.034)		(0.641)	(0.053)		(0.468)
Observations	99	70	19	319	110	74	49	100	352	99
Regional FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents estimates of the impact of the exposure to robots across demographic groups. Regressions are weighted by population in the start-of-period. The covariates and regional effects included in each model are indicated in the bottom rows. The list of covariates is documented in Appendix A. The missing geographic values in Germany are due to confidentiality-related data limitations. Statistical significance based on clustered standard errors (reported in parentheses) is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

computer technologies (Autor and Dorn, 2013; Autor *et al.*, 2003). An exception is Spain, where robots increased the demand for skilled workers. However, this increase seems to have taken place outside of the manufacturing: as shown in Table 4, robots reduced manufacturing employment in Spain but increased employment in other sectors. Unsurprisingly, we find that unskilled workers are more likely to have seen vanishing employment opportunities due to robots, notably in Germany and the United Kingdom.

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3.5 Pre-trends

In the previous sections, we have dealt with the potential threats of unknown local demand shocks and pre-existing trends to the identifying assumptions behind our estimates. However, we have not directly investigated whether the exposure to robots just picks up the variation of pre-exiting industry trends. We address this by regressing the change in the employment-to-population ratio before 1990, when industrial robots were rare and China was not yet integrated into the global economy, on both exposure variables. In Panel A of Table 7, we estimate the relationship between robots and the change in the employment-to-population ratio before 1990.[17] Reassuringly, we find that there are no significant pre-trends in line with our baseline results in Table 3. Furthermore, in Panel B, we control directly for the change in the employment-to-population ratio from the previous period on the right-hand side of our baseline specifications. This control has little impact on our estimates in general compared to those in Table 3.

Table 7 Accounting for pre-trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Denmark	Finland	France	Germany	Italy	Spain	Sweden	UK
	Panel A. Outcome variable: change in labour market outcomes in the previous period							
	1984-1994	1987-1993	1982-1990	1985-1995	1981-1991	1981-1991	1985-1993	1984-1991
Exposure to robots	-1.808	-0.684	-0.343	0.615***	-0.191	0.305*	0.063	-0.102
	(3.065)	(0.518)	(0.945)	(0.209)	(0.217)	(0.165)	(0.300)	(0.238)
Observations	99	70	19	323	110	49	100	352
	Panel B. Change in labour market outcomes in the previous period as a covariate							
Exposure to robots	1.077	-0.050	-0.381	-0.069	-0.418***	0.048	-0.450	-0.892*
	(1.234)	(0.428)	(0.636)	(0.044)	(0.137)	(0.070)	(0.502)	(0.525)
Observations	99	70	19	319	110	49	100	352
Regional FE	✓	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Panel A presents estimates of the change in the employment-to-population ratio in the previous period. For comparison with our main results, these outcomes are scaled equivalent change in exposure to robots. Panel B presents long-differences estimates for the baseline employment-to-population ratio controlling for the change in the employment-to-population ratio in the previous period. Regressions are weighted by population in the start-of-period. The covariates and regional effects included in each model are indicatedin the bottom rows. The list of covariates is documented in Appendix A. The missing geographic values in Germany are due to confidentiality-related data limitations. Statistical significance based on clustered standard errors (reported in parentheses) is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

[17] Due to data limitations related to industry employment data for earlier years, we have slightly different periods across countries. There is no data available before 1990 for Norway.

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4. Conclusions

In this paper, we examine how workers have fared from industrial robots and import competition from China in nine European countries: Denmark, Finland, France, Germany, Norway, Spain, Italy, Sweden and the United Kingdom. Overall, we find that robots have reduced employment in the manufacturing sector, while the impacts on local labour markets, which also take into account indirect employment effects, are more ambiguous. Local markets with a greater exposure to robots experienced significant employment losses in Italy, Norway and the United Kingdom. The coefficients for the remaining countries are imprecisely estimated, partly because employment losses in the manufacturing sector were offset by gains outside the manufacturing sector, most notably in Spain.[18] Unlike other computer technologies, which complement skilled workers in production (Autor and Dorn, 2013; Autor *et al*., 2003), we find that robots, which do not require an operator, had no significant impact on the demand for skilled workers. Spain is an exception, but also here, the increase in skilled employment seems to have taken place outside the manufacturing sector. Finally, we find that different demographic groups have fared differently from the robot revolution: in most countries, male and young workers have experienced most of the adverse impacts of robots in employment terms.

While we are unable to disentangle the factors underpinning the differential impacts of robots on employment across countries, our findings seem to be driven by factors beyond variation in labour market institutions. For example, while there is evidence that robots have reduced employment in the United States (Acemoglu and Restrepo, 2020), employment losses in the German manufacturing sector were offset by job creation in other sectors (Dauth *et al*., 2017). Dauth *et al*. (2017) suggest that the relative strength of German trade unions might explain the differential impacts of robots on jobs in the US and Germany.[19] However, our findings show that countries like Norway, with a relatively high union density, experienced significant employment declines as robots proliferated across the country. Indeed, even though the Nordic countries have similar labour market institutions, they have fared differentially from automation. In addition, while we find no evidence that robots have

[18] The heterogeneous impact of robot on European labour markets is further underlined by the wage analysis in Appendix B.

[19] In addition, Belloc et al. (2020) and Presidente (2020) study the impact of labour market institutions in explaining differences in investment in automation technologies.

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reduced employment in local labour markets across Germany, our findings suggest that import competition from China has. This begs the question why German trade unions better managed competition from robots than competition from China. We leave these questions for future research.

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Appendix A Data

A.1 Denmark

Employment data for the years 1994 to 2000 were acquired from Denmark Statistics. Our analysis uses total employees at the place of work aggregated to ISIC 2-digit industries and 99 municipalities (2007 version). Other local demographic characteristics and employment data are also collected from Denmark Statistics for the years 1984, 1994, 2000 and 2007, and where mapped using the municipality codes of the 2007 version for the years 1984, 1994, and 2000. Table 8 presents some summary statistics of outcome variables, controls and covariates.

A.2 Finland

Employment data for the years 1987 to 2007 were acquired from Finland Statistics. Our analysis uses total employees at the place of work aggregated to ISIC 2-digit industries and 70 sub-regions. Other local demographic characteristics and employment data are also collected from Finland Statistics, where they provide data with a consistent geographical unit for the years 1987, 1993, 2000 and 2007. Table 9 presents the summary statistics of outcome variables, other variables of interests, and covariates.

A.3 France

Local industry and demographic data are from the Population Census provided by IPUMS-International for the years 1982, 1990, 1999 and 2006 (Minnesota Population Center, 2020). IPUMS-International has provided data with consistent geographical boundaries, industry codes and education classifications across census years. Our analysis uses total employed aggregated to ISIC 2-digit industries and 22 NUTS 2 level units, excluding overseas regions. Table 10 presents the summary statistics of outcome variables, controls and covariates.

A.4 Germany

We use data from the anonymous Establishment History Panel, 1975-2018. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and/or remote data

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access.[20] The dataset covers all employees in the German labour market subject to social security, going back to 1975 for West Germany and 1992 for East Germany. The data encompasses detailed information on the composition of employment and average daily wages, including consistent industry codes and demographic characteristics such as age, gender and qualification. Our analysis uses total employees aggregated to ISIC 2-digit industries and 402 districts (Landkreise and kreisfreie Staedte) for the years 1985, 1995, and 2007. We also construct data of employment by demographic groups using BHP (1995-2007). Population data are collected from the German Federal Statistical Office for the years 1995 and 2007, where 1995 is the earliest available year at the district level.

A.5 Italy

Employment and industry data are collected from the Firm Census (Censimento generale dell'industria e dei servizi) for the years 1981, 1991, 2001 and 2011. Our analysis uses total employees from local business units, which include business, public and non-profit institutions, aggregated to ISIC 2-digit industries and 110 provinces (2009 version). Other local data are collected from the Population Census for the years 1981, 1991, 2001 and 2011, and aggregated at the province level by Istat in the Statistical Atlas of municipalities (Atlante statistico dei comuni). Demographic data is derived from the Population Census (1991-2011). Table 11 presents the summary statistics of outcome variables, controls and covariates.

A.6 Norway

Employment and industry data for the years 1995, 2000, and 2007, are collected from Norway Statistics. Our analysis uses total employed persons at the place of work aggregated to ISIC 2-digit industries and 74 economic regions (2018 version). Other local demographic characteristics and employment data are also collected from Norway Statistics, from which we aggregated detailed municipality codes into economic regions (2018 version) for the years 1995, 2000 and 2007. Employment data by demographic groups are only available after 2000. Table 12 shows the summary statistics of outcome variables, variables of interests and covariates.

[20] DOI: 10.5164/IAB.BHP7518.de.en.v1 (Ganzer *et al.*, 2020).

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A.7 Spain

Local industry and demographic data are from the Population Census provided by IPUMS-International (Minnesota Population Center, 2020), for the years 1981, 1991, 2001 and 2011. IPUMS International has provided data with consistent geographical boundaries, industry codes, and education classifications across census years. Our analysis uses total employment aggregated to ISIC 2-digit industries and 50 provinces (NUTS 3 level) excluding overseas regions (Table 13).

A.8 Sweden

Employment and industry data based on administrative sources (RAMS), for the years 1985 and years 1990 to 2007, are from Sweden Statistics. Our analysis uses the total gainfully employed population at the place of work aggregated to ISIC 2-digit industries and 100 local labour markets (1998 version). Other local demographic characteristics and employment data are also collected from Sweden Statistics, where the data is provided with consistent geographical units for the years 1985, 1993, 2000 and 2007. Table 14 presents some summary statistics.

A.9 United Kingdom

Employment and industry data are collected from the Business Register and Employment Survey (BRES) provided by NOMIS, which entails aggregated local labour markets data for consistent geographical units. Our analysis uses total employees aggregated to ISIC 2-digit industries in 352 local authority districts (prior to the April 2015 version) covering England, Scotland and Wales. Other local data are collected from Population Census for years 1981, 1991 and 2001, provided by NOMIS. Employment by demographic groups is constructed by using BRES for gender (1991-2007), while age and skill groups (1991-2011) are taken from Population Census. For the wage income analysis, weekly pay by gender is taken from the Annual Survey of Hours and Earnings, provided by NOMIS, for the years 1991 and 2007. Table 15 presents some summary statistics of relevant variables.

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Table 8 Summary Statistics: Denmark

	Summary Statistics				Means by quartiles of exposure to robots, IV				
	Mean	S.D.	Min.	Max.	All LMs	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables of interests									
Exposure to robots	1.151	0.580	0.184	3.014					
Exposure to Chinese imports*	1.822	1.475	0.030	11.988	48.185	28.793	52.192	59.617	60.764
Outcome variables, 1994-2007									
Change employment to population ratio	3.896	2.661	-3.774	20.235	3.896	3.725	4.083	4.134	3.683
Change manu. employment to population ratio	-2.080	1.679	-7.159	2.871	-2.080	-2.319	-2.064	-1.977	-1.847
Change non-manu. employment to population ratio	6.044	2.955	-1.896	24.060	6.044	6.115	6.202	6.195	5.593
Control variables, 1994									
Log population	11.193	0.869	4.718	13.055	11.193	11.749	11.143	10.798	10.817
Male population share	0.493	0.011	0.456	0.511	0.493	0.487	0.495	0.496	0.497
Population share above 65	0.154	0.031	0.050	0.255	0.154	0.163	0.145	0.158	0.148
Population share with high education	0.120	0.039	0.067	0.258	0.120	0.133	0.121	0.110	0.106
Foreign born population share	0.016	0.011	0.000	0.046	0.016	0.024	0.015	0.012	0.012
Employment share in light manu.	0.028	0.024	0.000	0.220	0.028	0.026	0.033	0.029	0.024
Employment share in construction	0.062	0.019	0.000	0.121	0.062	0.053	0.067	0.063	0.067
Employment share in mining	0.001	0.003	0.000	0.020	0.001	0.001	0.002	0.002	0.001
Female employment share in manu.	0.313	0.055	0.123	0.889	0.313	0.319	0.303	0.321	0.311

Notes: Columns 1-4 report the basic summary statistics at the local labour market level. Column 6-9 present means for all labour markets as well as the quartiles of the robot IV variable from equation 4. The means are weighted by population at the start of the period; *the country's exposure to Chinese imports is reported in column 1-4 and the IV exposure to Chinese imports in column 5-9.

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Table 9 Summary Statistics: Finland

	Summary Statistics				Means by quartiles of exposure to robots, IV				
	Mean	S.D.	Min.	Max.	All LMs	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables of interests									
Exposure to robots	1.308	0.708	0.141	4.766					
Exposure to Chinese imports*	2.927	2.316	0.042	16.403	54.390	28.590	47.593	62.933	70.920
Outcome variables, 1993-2007									
Change employment to population ratio	7.122	2.117	-7.149	10.903	7.122	5.316	7.644	7.435	6.504
Change manu. employment to population ratio	0.467	1.601	-2.656	4.805	0.467	0.747	0.143	1.001	0.384
Change non-manu. employment to population ratio	7.075	2.626	-2.830	11.718	7.075	4.912	7.978	6.774	6.552
Control variables, 1993									
Log population	11.924	1.349	7.786	13.966	11.924	10.590	12.720	11.539	11.332
Male population share	0.486	0.010	0.474	0.522	0.486	0.499	0.483	0.488	0.487
Population share above 65	0.139	0.025	0.099	0.248	0.139	0.140	0.126	0.150	0.152
Population share with high education	0.159	0.042	0.071	0.222	0.159	0.125	0.183	0.143	0.145
Foreign born population share	0.013	0.009	0.003	0.045	0.013	0.007	0.018	0.009	0.010
Employment share in light manu.	0.047	0.035	0.000	0.215	0.047	0.028	0.040	0.064	0.051
Employment share in construction	0.047	0.007	0.030	0.081	0.047	0.049	0.046	0.048	0.047
Employment share in mining	0.003	0.004	0.000	0.039	0.003	0.006	0.002	0.002	0.002
Female employment share in manu.	0.326	0.043	0.192	0.483	0.326	0.309	0.338	0.318	0.318

Notes: Columns 1-4 report the basic summary statistics at the local labour market level. Column 6-9 present means for all labour markets as well as the quartiles of the robot IV variable from equation 4. The means are weighted by population at the start of the period; *the country's exposure to Chinese imports is reported in column 1-4 and the IV exposure to Chinese imports in column 5-9.

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Table 10 Summary Statistics: France

	Summary Statistics				Means by quartiles of exposure to robots, IV				
	Mean	S.D.	Min.	Max.	All LMs	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables of interests									
Exposure to robots	0.954	0.644	0.114	4.056					
Exposure to Chinese imports*	1.092	0.327	0.148	1.723	6.025	4.944	5.614	7.300	6.981
Outcome variables, 1990-2006									
Change employment to population ratio	1.987	1.163	0.092	4.580	1.987	1.321	2.871	1.774	2.878
Change manu. employment to population ratio	-2.053	0.878	-3.279	-0.085	-2.053	-2.128	-1.167	-2.464	-2.148
Change non-manu. employment to population ratio	4.446	0.732	3.542	6.099	4.446	3.790	4.591	4.670	5.404
Control variables, 1990									
Population share above 65	0.139	0.026	0.108	0.209	0.139	0.141	0.157	0.138	0.122
Population share with high education	0.087	0.031	0.057	0.145	0.087	0.114	0.066	0.074	0.067
Employment share in light manu.	0.028	0.006	0.008	0.037	0.028	0.025	0.027	0.032	0.032
Employment share in construction	0.075	0.008	0.063	0.112	0.075	0.076	0.076	0.075	0.070
Employment share in mining	0.003	0.004	0.000	0.020	0.003	0.003	0.001	0.001	0.007

Notes: Columns 1-4 report the basic summary statistics at the local labour market level. Column 6-9 present means for all labour markets as well as the quartiles of the robot IV variable from equation 4. The means are weighted by population at the start of the period; *the country's exposure to Chinese imports is reported in column 1-4 and the IV exposure to Chinese imports in column 5-9.

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Table 11 Summary Statistics: Italy

	Summary Statistics				Means by quartiles of exposure to robots, IV				
	Mean	S.D.	Min.	Max.	All LMs	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables of interests									
Exposure to robots	2.244	1.768	0.404	9.202					
Exposure to Chinese imports*	1.536	0.737	0.277	3.610	9.984	5.701	7.608	10.942	13.672
Outcome variables, 1991-2011									
Change employment to population ratio	1.403	2.311	-4.378	5.920	1.403	2.746	1.768	0.679	0.775
Change manu. employment to population ratio	-2.699	2.027	-9.067	0.883	-2.699	-1.170	-1.863	-3.058	-3.997
Change non-manu. employment to population ratio	4.102	2.329	-2.230	11.035	4.102	3.916	3.631	3.737	4.773
Control variables, 1991									
Log population	13.513	0.907	11.001	15.140	13.513	13.581	13.132	13.257	13.876
Male population share	0.485	0.005	0.464	0.500	0.485	0.485	0.486	0.485	0.485
Population share above 65	0.153	0.033	0.097	0.237	0.153	0.149	0.160	0.163	0.145
Population share with high education	0.211	0.043	0.117	0.314	0.211	0.219	0.204	0.206	0.213
Employment share in light manu.	0.068	0.060	0.006	0.426	0.068	0.055	0.055	0.087	0.072
Employment share in construction	0.076	0.023	0.048	0.173	0.076	0.079	0.083	0.078	0.070
Employment share in mining	0.003	0.005	0.000	0.079	0.003	0.003	0.004	0.003	0.002
Female employment share in manu.	0.088	0.052	0.018	0.242	0.088	0.055	0.069	0.110	0.105

Notes: Columns 1-4 report the basic summary statistics at the local labour market level. Column 6-9 present means for all labour markets as well as the quartiles of the robot IV variable from equation 4. The means are weighted by population at the start of the period; *the country's exposure to Chinese imports is reported in column 1-4 and the IV exposure to Chinese imports in column 5-9.

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Table 12 Summary Statistics: Norway

	Summary Statistics				Means by quartiles of exposure to robots, IV				
	Mean	S.D.	Min.	Max.	All LMs	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables of interests									
Exposure to robots	0.312	0.353	0.056	4.336					
Exposure to Chinese imports*	1.901	1.022	0.180	5.027	64.553	42.439	51.373	73.746	100.384
Outcome variables, 1995-2007									
Change employment to population ratio	12.043	2.683	1.201	22.071	12.043	12.800	13.821	11.279	10.397
Change manu. employment to population ratio	-0.791	1.200	-9.336	5.459	-0.791	-0.788	-0.450	-0.706	-1.311
Change non-manu. employment to population ratio	12.609	2.233	7.178	21.627	12.609	13.309	14.060	11.792	11.502
Control variables, 1995									
Log population	11.404	1.103	8.822	13.089	11.404	11.780	10.966	11.592	10.763
Male population share	0.494	0.009	0.476	0.518	0.494	0.489	0.500	0.495	0.496
Population share above 65	0.159	0.025	0.101	0.229	0.159	0.159	0.148	0.156	0.179
Population share with high education	0.152	0.054	0.082	0.298	0.152	0.201	0.125	0.138	0.116
Foreign born population share	0.057	0.036	0.013	0.140	0.057	0.085	0.046	0.044	0.041
Employment share in light manu.	0.031	0.018	0.002	0.126	0.031	0.030	0.028	0.030	0.039
Employment share in construction	0.057	0.012	0.027	0.093	0.057	0.050	0.057	0.062	0.059
Employment share in mining	0.010	0.021	0.000	0.090	0.010	0.005	0.032	0.008	0.002

Notes: Columns 1-4 report the basic summary statistics at the local labour market level. Column 6-9 present means for all labour markets as well as the quartiles of the robot IV variable from equation 4. The means are weighted by population at the start of the period; *the country's exposure to Chinese imports is reported in column 1-4 and the IV exposure to Chinese imports in column 5-9.

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Table 13 Summary Statistics: Spain

	Summary Statistics				Means by quartiles of exposure to robots, IV				
	Mean	S.D.	Min.	Max.	All LMs	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables of interests									
Exposure to robots	2.221	1.718	0.257	12.098					
Exposure to Chinese imports*	1.632	0.957	0.176	3.840	17.007	6.840	10.481	13.182	26.021
Outcome variables, 1991-2011									
Change employment to population ratio	4.053	1.750	0.531	7.605	4.053	3.908	2.955	3.329	4.960
Change manu. employment to population ratio	-3.190	1.856	-6.630	0.252	-3.190	-1.373	-2.342	-2.909	-4.453
Change non-manu. employment to population ratio	7.500	2.339	1.499	11.054	7.500	5.609	5.583	6.491	9.630
Control variables, 1991									
Log population	13.986	1.000	10.948	15.407	13.986	13.371	13.462	13.702	14.614
Male population share	0.490	0.006	0.479	0.509	0.490	0.491	0.495	0.492	0.487
Population share above 65	0.137	0.026	0.082	0.223	0.137	0.144	0.140	0.144	0.130
Population share with high education	0.054	0.017	0.032	0.088	0.054	0.047	0.043	0.047	0.067
Foreign born population share	0.021	0.014	0.002	0.168	0.021	0.029	0.021	0.015	0.020
Employment share in light manu.	0.053	0.035	0.004	0.141	0.053	0.029	0.060	0.045	0.065
Employment share in construction	0.111	0.022	0.063	0.175	0.111	0.130	0.121	0.119	0.094
Employment share in mining	0.009	0.016	0.002	0.086	0.009	0.006	0.014	0.015	0.005
Female employment share in manu.	0.225	0.052	0.116	0.339	0.225	0.227	0.237	0.208	0.229

Notes: Columns 1-4 report the basic summary statistics at the local labour market level. Column 6-9 present means for all labour markets as well as the quartiles of the robot IV variable from equation 4. The means are weighted by population at the start of the period; *the country's exposure to Chinese imports is reported in column 1-4 and the IV exposure to Chinese imports in column 5-9.

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Table 14 Summary Statistics: Sweden

	Summary Statistics				Means by quartiles of exposure to robots, IV				
	Mean	S.D.	Min.	Max.	All LMs	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables of interests									
Exposure to robots	0.997	0.618	0.126	5.821					
Exposure to Chinese imports*	0.790	0.376	0.183	2.962	29.846	18.377	28.686	33.932	32.761
Outcome variables, 1993-2007									
Change employment to population ratio	4.956	1.625	-0.918	12.428	4.956	4.735	4.657	4.989	5.717
Change manu. employment to population ratio	-0.184	1.492	-7.775	7.187	-0.184	-0.206	-0.810	0.613	0.413
Change non-manu. employment to population ratio	5.397	1.551	-1.182	10.590	5.397	4.996	5.855	4.465	5.523
Control variables, 1993									
Log population	12.464	1.522	8.155	14.520	12.465	10.835	13.230	11.669	12.214
Male population share	0.494	0.006	0.487	0.528	0.494	0.501	0.491	0.495	0.497
Population share above 65	0.176	0.022	0.127	0.268	0.176	0.185	0.168	0.185	0.179
Population share with high education	0.143	0.038	0.059	0.195	0.143	0.121	0.161	0.122	0.130
Foreign born population share	0.058	0.026	0.011	0.246	0.058	0.030	0.069	0.046	0.058
Employment share in light manu.	0.033	0.019	0.001	0.167	0.033	0.044	0.033	0.029	0.032
Employment share in construction	0.060	0.007	0.026	0.092	0.060	0.065	0.058	0.063	0.056
Employment share in mining	0.002	0.012	0.000	0.161	0.002	0.014	0.001	0.002	0.001
Female employment share in manu.	0.278	0.039	0.119	0.406	0.278	0.252	0.291	0.268	0.269

Notes: Columns 1-4 report the basic summary statistics at the local labour market level. Column 6-9 present means for all labour markets as well as the quartiles of the robot IV variable from equation 4. The means are weighted by population at the start of the period; *the country's exposure to Chinese imports is reported in column 1-4 and the IV exposure to Chinese imports in column 5-9.

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Table 15 Summary Statistics: United Kingdom

	Summary Statistics				Means by quartiles of exposure to robots, IV				
	Mean	S.D.	Min.	Max.	All LMs	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables of interests									
Exposure to robots	0.302	0.591	-0.137	6.255					
Exposure to Chinese imports*	2.443	1.330	0.018	7.835	6.381	4.155	6.097	7.265	8.074
Outcome variables, 1991-2007									
Change employment to population ratio	2.172	4.321	-8.047	18.911	2.172	2.181	2.063	3.235	1.444
Change manu. employment to population ratio	-2.591	1.827	-9.325	6.013	-2.591	-1.761	-2.265	-2.721	-3.561
Change non-manu. employment to population ratio	7.034	3.924	-5.196	21.153	7.034	6.983	6.542	7.904	6.834
Control variables, 1991									
Log population	12.293	0.925	7.627	14.295	12.293	12.513	12.251	11.966	12.366
Male population share	0.484	0.007	0.450	0.506	0.484	0.479	0.484	0.486	0.487
Population share above 65	0.161	0.028	0.098	0.307	0.161	0.166	0.165	0.159	0.153
Population share with high education	0.118	0.040	0.040	0.260	0.118	0.135	0.128	0.109	0.102
Foreign born population share	0.069	0.068	0.009	0.318	0.069	0.092	0.078	0.043	0.059
Asian population share	0.033	0.046	0.000	0.249	0.033	0.032	0.043	0.017	0.039
Black population share	0.016	0.031	0.000	0.163	0.016	0.030	0.012	0.006	0.014
White population share	0.945	0.075	0.705	0.997	0.945	0.930	0.939	0.974	0.943
Employment share in light manu.	0.332	0.153	0.000	0.825	0.332	0.427	0.335	0.341	0.232
Employment share in construction	0.049	0.017	0.016	0.155	0.049	0.049	0.047	0.050	0.051
Employment share in mining	0.007	0.018	0.000	0.191	0.007	0.005	0.008	0.010	0.007
Female employment share in manu.	0.303	0.058	0.000	0.498	0.303	0.319	0.309	0.313	0.276

Notes: Columns 1-4 report the basic summary statistics at the local labour market level. Column 6-9 present means for all labour markets as well as the quartiles of the robot IV variable from equation 4. The means are weighted by population at the start of the period; *the country's exposure to Chinese imports is reported in column 1-4 and the IV exposure to Chinese imports in column 5-9.

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Appendix B Robots and wages

Consistent wage data on the local level is sparse for most countries. Nonetheless, in the below, we compile annual wage income data for Denmark, Norway and Sweden, from their respective national statistics offices. For Germany, we use the median of daily wages of full-time equivalent employees from the IAB. For the UK, median weekly pay is taken from NOMIS. Following the existing literature (Acemoglu and Restrepo, 2020; Dauth *et al*., 2017; Dottori, 2020), we augment the observations by multiplying the demographic cells. Table 16 presents the baseline results with the same specifications from panel B and D of Table 3. The 2SLS results from Panel B suggest that local labour markets with a greater exposure to robots saw wage income decline in Finland, Germany and Sweden, although most coefficients are imprecisely estimated. In contrast, we find that wage income in Denmark increased as robots were adopted. We note higher wages might reflect higher productivity gains from robots in some countries, offsetting the displacement effect. Our wage analysis underlines the takeaway from our main analysis, which is that the impact of robots on local labour markets is highly heterogeneous across Europe.

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Table 16 The wage effects of robots

	(1)	(2)	(3)	(4)	(5)
	Denmark	Norway	Germany	Sweden	UK
	Annual wage income, 1994-2007	Annual wage income, 1995-2007	Daily wage, 1995-2007	Annual wage income, 1993-2007	Weekly pay, 1991-2007
			Panel A. OLS		
Exposure to robots	0.014**	-0.019**	0.0133	-0.008	-0.002
	(0.006)	(0.008)	(0.068)	(0.006)	(0.007)
Exposure to Chinese imports	0.003	0.000	0.057	0.022*	-0.008*
	(0.002)	(0.004)	(0.068)	(0.010)	(0.005)
Observations	196	148	2443	200	594
			Panel B. 2SLS		
Exposure to robots	0.026**	-0.034***	-0.053	-0.007	0.009
	(0.011)	(0.011)	(0.033)	(0.007)	(0.010)
Exposure to Chinese imports	-0.003	-0.001	0.007	0.014	0.002
	(0.002)	(0.005)	(0.068)	(0.021)	(0.007)
Observations	196	148	2247	200	594
Regional FE	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓

Notes: This table presents OLS and 2SLS estimates of the impact of the exposure to robots and Chinese import competition on wage. The outcome variables are log difference of wage. Observations are augmented by demographic cells (gender for all countries. Germany has extra 3 age groups and 2 education groups) Regressions are weighted by population in the start-of-period. The covariates and regional effects included in each model are indicated in the bottom rows. The list of covariates is documented in Appendix A. Statistical significance based on clustered standard errors (reported in parentheses) is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

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