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Industrial Robots, and Information and Communication Technology:

The Employment Effects in EU Labour Markets

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Abstract

This paper explores the effects of industrial robots and information and communication technology (ICT) on regional employment in EU countries. The empirical analysis relies on a harmonised comprehensive regional dataset, which combines business statistics and national and regional accounts data. This rich dataset enables us to provide detailed insights into the employment effects of automation and computerisation in EU regions for the period 2001-2016. The results suggest relatively weak effects on regional total employment dynamics. However, employment effects differ between manufacturing and non-manufacturing industries. Industrial robots show negative employment effects in local manufacturing industries, but positive employment effects in local non-manufacturing industries. While the negative effect is concentrated in particular local manufacturing industries, the positive effect operates in local service industries. IT investments show positive employment effects only in local manufacturing industries, while CT investments are shown to be irrelevant for employment dynamics. In contrast, software and database investments have had a predominantly negative impact on local employment in both local manufacturing and non-manufacturing industries.

Keywords: Industrial robots, ICT, EU labour markets, employment effects

JEL classification: J23, L60, O33, R11

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1 Introduction

The question of how technological advances affect employment has been debated throughout history (Keynes, 1930). Recently, the effects of robotics, digitisation, computerisation and artificial intelligence (AI) have attracted much attention. As new technologies aim to perform work processes fully or in part, they can substitute human labour. For this reason, concerns have been raised that the use of advanced automation technologies can produce lay-offs and unemployment on a large scale. Some studies present alarming numbers of jobs that are at risk of being automated and replaced in the near future (e.g., Frey & Osborne, 2017; OECD, 2019; World Bank, 2016). However, as suggested by previous waves of technological progress, even though jobs are destroyed through automation, others can be created (e.g., Acemoglu & Restrepo, 2020b; Autor, 2015; Bessen, 2019). Accordingly, the repercussions on employment induced by automation are far from clear-cut.

This paper empirically analyses the effects of industrial robots and information and communication technology (ICT) on regional employment in EU countries by adopting a local labour market approach (Acemoglu & Restrepo, 2018; Dauth, Findeisen, Suedekum, & Woessner, 2019). I combine business statistics and national as well as regional accounts data to construct a harmonised regional industry-specific employment dataset. By utilising these rich data, this study presents novel findings on the repercussions of automation and computerisation for employment in EU labour markets. Importantly, the detailed dataset also provides insights into heterogeneous effects on employment across individual local industries. The results do not support the findings of previous studies on effects of automation in EU regions, but are consistent with recent findings for individual EU countries that rely on comprehensive administrative data.

Acemoglu and Restrepo (2019) provide a theoretical framework for disentangling the effects of automation technologies (see also Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2018).[1] Although recent studies primarily focus on industrial robots in relation to automation, the present study also puts a particular spotlight on investments in different ICT items and considers them as a different type of automation technology.[2] In general, automation generates a displacement and a productivity effect. Automation technologies are deployed to take over tasks previously performed by human labour (Acemoglu & Restrepo, 2020b; Autor, 2015). As routine cognitive and routine manual tasks are particularly liable to be fully automated (Autor, Levy, & Murnane, 2003), the introduction of automation technologies seems to be associated with a declining demand for labour in medium(-skilled) occupations (Autor & Dorn, 2013; Goos, Manning, & Salomons, 2014). However, the productivity effect counteracts the displacement effect. Automation can reduce production costs and increase value added, which pushes up the demand for labour in complementary non-automated tasks (Acemoglu & Restrepo, 2019; Autor, 2015) and impacts employment in upstream and downstream industries (Bessen, Goos, Salomons, & van den Berge, 2020).[3] In addition, new technologies can create new labour-intensive tasks that raise labour demand (Acemoglu & Restrepo, 2019; Bessen, 2015). The net employment effect of automation on employment therefore depends on the strength of the displacement

[1] For an overview of different theoretical approaches on the employment effects of automation see Barbieri, Mussida, Piva, and Vivarelli (2019).

[2] Similar to industrial robots, ICT technology helps to automate particular tasks in production and service processes. Thus, ICT technology can also be related to replacement and productivity effects as discussed above.

[3] The productivity effect also corresponds to a positive income effect. As automation increases the overall output, national income becomes larger, which translates into a higher aggregated demand, which is accompanied by positive repercussions for employment (Bessen et al., 2020).

effect and the countervailing effects.

A very rich strand in the empirical literature has emerged that examines the labour market outcomes of automation. This line of research can be categorised by the aggregation level of the empirical analyses. A number of studies explore the effects of robots and ICT at the sectoral level (e.g., De Vries, Gentile, Miroudot, & Wacker, 2020; Ghodsi, Reiter, Stehrer, & Stöllinger, 2020; Graetz & Michaels, 2018), while others analyse effects in local labour markets (e.g., Acemoglu & Restrepo, 2020a; Anton et al., 2020; Dauth et al., 2019; Dottori, 2021; Gaggl & Wright, 2017). Even though there are results that suggest a negative (for instance Acemoglu & Restrepo, 2020a, in their seminal paper on local labour markets in the US) and positive net impact on total employment (Kariel, 2021), most studies that use regional data on individual countries find heterogeneous employment effects across manufacturing and service industries and population subgroups without large repercussions on total employment. Empirical analyses that consider a set of regions from different EU countries find evidence for negative longer term effects on the total employment rate (Anton et al., 2020; Chiacchio, Petropoulos, & Pichler, 2018). Most recently, researchers have started to put a spotlight on the effects of automation relying on different sources of firm-level data. The results of these studies are also inconclusive, as evidence ranges from positive (e.g., Aghion, Antonin, Bunel, & Jaravel, 2020) and negative effects on firms' employment (e.g., Bessen, 2019) to mixed effects for adopting and non-adopting firms (e.g., Acemoglu, Lelarge, & Restrepo, 2020; Koch, Manuylov, & Smolka, 2021).

This paper contributes to this literature by analysing the effects of industrial robots and ICT on regional employment in EU regions. Only a small number of previous studies have assessed the labour market effects of robots and ICT at the regional level, using data on multiple European countries. In general, limitations concerning data availability and data quality make it difficult to apply reliable regional industry-specific employment data in a cross-country perspective. Anton et al. (2020) draw primarily on several ad-hoc requests for the *European Union Labour Force Survey* (EU-LFS) data and Chiacchio et al. (2018) rely on regional employment data by industry covering six European countries taken from the *Structural Business Statistics* (SBS) from Eurostat. The EU-LFS data do not seem to be well designed to capture the economic activity structure disaggregated at the regional level, and initial SBS data are subject to missing values and are not harmonised over time. The present study exploits information from a newly constructed harmonised regional dataset that captures employment by industry at a disaggregated level. To the best of my knowledge, this is the first study that uses a fully harmonised dataset on EU NUTS-2 regions to analyse the employment effects of automation.[4] Similar to Chiacchio et al. (2018), I rely on SBS employment data, but further link them to national accounts and regional accounts data to balance the employment information provided in the different data sources. Importantly, the resulting harmonised regional industry-specific employment data incorporate the most reliable sources of regional employment that are currently available. Moreover, the rich dataset also allows insights into heterogeneous effects on employment across individual industries in EU regions. This approach allows us to identify the most affected industries at a granular level. As a further contribution, this study goes beyond the focus on the effects of industrial robots, and also investigates employment effects of different ICT investments. This is the first study that exploits detailed industry-level information about IT, CT, and software and database capital stocks for EU countries.

[4]The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia, but includes regions from the United Kingdom.

The results suggest relatively weak effects on total employment dynamics in EU regions for the period 2001-2016. However, the effects reveal differences between manufacturing and non-manufacturing industries. Industrial robots show negative employment effects in local manufacturing industries, but indicate positive employment effects in local non-manufacturing industries. While the negative effect is concentrated in particular local manufacturing industries, the positive effect operates in local service industries. IT investments only show positive employment effects in local manufacturing industries, while CT investments are revealed to be irrelevant for employment dynamics. In contrast, investments in software and databases indicate a predominantly negative impact on local employment in both local manufacturing and non-manufacturing industries. As a result, the effects of software and database investments are the only effects that can be observed for total employment.

The remainder of this paper is structured as follows. Section 2 provides an overview of the data sources and discusses the data preparation steps. Section 3 discusses the empirical strategy applied in this study. A descriptive analysis provides first insights into the relationship between automation and employment in Section 4, while Section 5 presents the results of the econometric analysis. Robustness checks are provided in Section 6. Finally, Section 7 sets out the conclusions.

2 Data and data preparation

2.1 Employment data

I make use of different data sources for employment and apply several steps to prepare the data and construct a harmonised dataset on regional employment. Before I discuss the data processing in detail, I give a general overview of employment data used in this analysis.

Regional employment data by industry are taken from the Structural Business Statistics (SBS) data. SBS data do not only rely upon statistical surveys, but also include information from business registers and administrative sources. Eurostat provides two data files that cover the period 1995-2007 and after 2008 and include principally employment information for 2-digit industries in EU regions down to the NUTS-2 level. Beyond the fact that the data are not harmonised over time, the data source is also subject to limitations when it comes to data availability and data coverage. In particular, non-manufacturing industries show a relatively large proportion of missing employment data. Furthermore, the SBS data do not cover all industries. Information about employment in agriculture, forestry and fishing, public administration, and non-market services (education and health) is not available. Furthermore, there are missing values over time in particular in non-manufacturing industries. Nonetheless, as SBS data provide rich information about regional employment with detailed breakdowns, they are used as the primary source for regional employment data by industry.

Other industry-level employment data are drawn from national accounts and regional accounts. National accounts data from Eurostat report detailed employment information at the 2-digit industry level (NACE Rev. 2) for EU economies and is principally available for the period from 1995 onwards. Regional accounts data come from the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO). This database generally provides a set of long-time series indicators for EU regions. Importantly, it also contains employment data at the NUTS-2 level (reference-year 2016), although at a rather aggregated industry level (NACE Rev. 2). The regional accounts data distinguish between the industry groups *A*, *B-E*, *F*, *G-J*, *K-N* and *O-U*.

Harmonised regional employment data by industry are constructed by combining information from the SBS data with national accounts as well as regional accounts data. In a first step, the initial SBS data are harmonised over time. At the regional level, data are transformed to match the NUTS codes from 2016, while at the industry level, data are adjusted to correspond to the NACE Rev.2 codes. While employment data in the manufacturing industry are prepared at the 2-digit industry level, other non-manufacturing industries are used at the 1-digit industry level owing to data limitations. Missing data are imputed, based on employment dynamics at the NUTS-1 level and dynamics obtained from regional accounts employment data, and interpolation techniques. In a final step, the harmonised and filled SBS data are combined with industry-level employment data from national accounts and regional accounts. While national accounts provide information about employment at 2-digit industry level, regional accounts report regional employment data only for aggregated industry categories. In order to use information from both data sources, I apply the RAS method, which is an iterative scaling method. In doing so, the employment data in the SBS are rescaled in an iterative sequence such that the sums in countries and regions across the defined industries converge to the corresponding sums in the national and regional accounts. The resulting dataset provides harmonised information for the period 1995-2016.

2.2 Further data

In addition to the employment data, I draw on data from different sources for information about the socio-demographic structure in EU regions, and to obtain information about robots, ICT and trade.

Regional socio-demographic data are taken from the publicly available EU-LFS based data from Eurostat. Specifically, I use information about the gender, educational attainment, age cohort and country of birth structure within EU regions. In general, this data source provides information from 2000 onwards.

Data on industrial robots are drawn from the International Federation of Robotics (IFR) database, which offers counts of the stock of multi-purpose robots for 50 countries from 1993 to 2016 with detailed breakdowns in manufacturing industries (even 3-digit industry level data are available for a set of industries) and more aggregated divisions in non-manufacturing industries. However, with the exception of Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden and the UK, the data only provide country totals of robot counts until 2004. As the present analysis looks at the period from 2001 onwards, I impute the distribution of robots across industries in 2001 using the first available year of 2004 in the other European countries. The data are collected via yearly surveys of robot suppliers. The IFR data have become one of the main sources for information about fully autonomous multi-purpose machines in the empirical literature. The dataset includes aggregated information about the non-manufacturing industries agriculture, forestry and fishing; mining and quarrying; electricity, gas and water supply; construction; and research and development. In this study, manufacturing industries in the IFR data are principally matched at the 2-digit industry level, while other non-manufacturing industries are linked at a more aggregated industry level. The IFR data also report the number of robots for *all other manufacturing branches*, *all other non-manufacturing branches* and *unspecified*. The former is allocated to the remaining manufacturing industries without any direct match in the IFR data (i.e. manufacturing of furniture, other manufacturing, repair and installation of machinery and equipment – C31-C33); while the latter is ascribed to the remaining non-manufacturing industries without a match in the IFR data. Unfortunately, the share of robots with a missing industry assignment (i.e. *unspecified*) varies considerably across EU countries. I follow Acemoglu and Restrepo (2018) and allocate the number of unspecified robots proportionally across industries without altering the initial distribution of robots within countries.

ICT data are taken from the EU KLEMS Growth and Productivity Accounts that provide information about input categories such as capital (K), labour (L), energy (E), material (M) and service inputs (S) at the industry level. The most recent edition of the EU KLEMS is the EU KLEMS Release 2019.[5] It provides measures of economic growth, productivity, employment, gross-fixed capital formation, and technological change at the industry level (NACE Rev. 2) for all EU countries, Japan, and the United States. However, the breakdown of industries is different across countries.[6] For this analysis, I use information about capital stocks related to information and communication technology (ICT). Specifically, EU KLEMS allows to distinguish between three different ICT capital stock items:

[5] https://euklems.eu

[6] For instance, Austria provides information about 19 manufacturing industries, while data for the Netherlands include only 13 manufacturing industries.

computer hardware (IT), telecommunication equipment (CT), and computer software and databases (Software & Database). However, the coverage of indicators and the granularity of information in the EU KLEMS data vary across countries. The data are therefore supplemented by using additional data from the European System of National Accounts (ESA) provided by Eurostat.[7] Unfortunately, there are a number of countries for which information for the three ICT capital stock items is present neither in the EU KLEMS database, nor in the ESA data. Bulgaria, Hungary, Ireland, Poland, Portugal, Slovenia, and Lithuania all lack detailed information.[8] In order to have information available for all EU countries, data imputations are conducted. A detailed description about the imputation procedure is provided in the Appendix A.1. The final dataset provides detailed industry-level information about ICT capital stocks deflated to 2010 prices in euros, which covers EU countries for the period 1995-2017.

Trade data with China are extracted from the UN Comtrade database. These data provide information about exports and imports vis-à-vis China for EU countries and 29 industries (2-digit level for manufacturing industries) principally covering the period 1995-2020. UN Comtrade database also reports trade data that cannot be ascribed directly to an industry. These unspecified exports and imports with China are allocated proportionally across the available trade flows in industries, which does not change the initial distribution across industries. Both exports and imports are deflated to 2010 prices in euros.

[7] For some countries (Germany, Spain and Romania) detailed data were published at the time the EU KLEMS Release 2019 was set up but are no longer provided by Eurostat.

[8] Denmark does not report information about the capital stock regarding computer software and databases. These data are also imputed.

3 Empirical strategy

In this study, I aim to analyse the effects of automation on regional employment in EU countries. To do so, I build on the innovative local level approach introduced by Acemoglu and Restrepo (2018). This approach has been adopted in a large set of empirical analyses (e.g., Anton et al., 2020; Chiacchio et al., 2018; Dauth et al., 2019; Dottori, 2021; Kariel, 2021). Acemoglu and Restrepo (2018) base their empirical setting on a micro-founded theoretical model, in which they derive the full equilibrium impact of automation on the local labour market. This equilibrium effect at the local level comprises the direct effects of automation in local industries, and its spillover effects arising from directly and indirectly affected industries. A total negative effect implies that the direct negative replacement effect predominates over the positive productivity and other spillover effects. In contrast, a total positive effect suggests that the productivity and spillover effects exceed the replacement effect. This analysis follows this approach and evaluates the equilibrium effect of industrial robots and ICT on regional employment dynamics.

3.1 Breakdown of industry-level data to regions

Information about industrial robots and ICT is initially available at the industry level. In order to capture the regional exposure to automation, the variables need to be broken down to the regional level. Following Acemoglu and Restrepo (2018), information about industrial robots and ICT is mapped to regions by using regional employment data by industry. This approach is based on the assumption that the labour market effects of robots and ICT depend on the local industry structure. Therefore, differences in the regional industry and thus employment structure result in differences in the exposure to automation and consequently in different labour market outcomes. I construct the change in the regional robot exposure in a region r and a country c, $\Delta Robots_{r,c}$, in the following way:

$$\Delta Robots_{r,c} = \sum_{j=1}^{J} \left(\frac{EMP_{r,j,c}}{EMP_{r,c}} \times \frac{\Delta Robots_{j,c}}{EMP_{j,c}} \right). \tag{1}$$

$EMP_{r,j,c}$ denotes the number of employed individuals in industry j in region r and country c, while $EMP_{j,c}$ and $EMP_{r,c}$ are the total employment numbers by industry and region, respectively. $\Delta Robots_{j,c}$ is the change in the number of industrial robots in an industry j over time. As can be seen, the industry-specific change in robot exposure is divided by the country-wide employment number in this industry. This intensity is then multiplied by the regional employment numbers in this specific industry and finally rescaled by the total employment numbers in regions. The sum over all local industries (J) gives the change in the overall robot exposure. All employment numbers refer the base year 1995, which is the first available year in the harmonised regional employment data.

I apply the same approach to construct the change in the regional exposure to ICT investments in a region r and a country c denoted by $\Delta ICT_{r,c}$:

$$\Delta ICT_{r,c} = \sum_{j=1}^{J} \left(\frac{EMP_{r,j,c}}{EMP_{r,c}} \times \frac{\Delta ICT_{j,c}}{EMP_{j,c}} \right). \tag{2}$$

Importantly, ICT covers three different capital stock items: computer hardware (IT), telecommunication equipment (CT), and computer software and databases (Software & Database). Thus, $ICT \in \{IT, CT, Software\&Database\}$. Again, the employment data are taken from the base year 1995. Figure B.1 in the Appendix illustrate that ICT capital stocks are relatively pronounced in non-manufacturing industries. As the regional industry-level employment data used in Equation 2 only provide employment data at the 1-digit industry level for local non-manufacturing industries, a large proportion of the change in ICT capital stocks is allocated to regions based on aggregated employment data. I acknowledge that this is a limitation of the study. An allocation based on a more granular level of non-manufacturing local industries would allow more reliable estimates for the employment effects of ICT investments.

3.2 Econometric approach

To empirically explore employment effects of automation in the form of industrial robots and ICT, I employ an econometric analysis. More specifically, I look at the changes in the regional exposure to industrial robots and ICT, and evaluate whether those are associated with regional employment dynamics. This analysis focuses on long-term changes between the years 2001 and 2016.[9] Following Acemoglu and Restrepo (2018) and Dauth et al. (2019) (for further applications see Anton et al., 2020; Dottori, 2021; Kariel, 2021), I estimate the following baseline specification:

$$\Delta EMP_{r,c} = \gamma_1 \cdot \Delta Robots_{r,c} + \gamma_2 \cdot \Delta ICT_{r,c} + \gamma_3 \cdot \Delta TradeChina_{r,c} + \boldsymbol{X}'_{\boldsymbol{r,c}}\boldsymbol{\beta} + \mu_c + \epsilon_{r,c}, \qquad (3)$$

where $\Delta EMP_{r,c}$ is the change in the employment outcome in region r in country c over the period 2001-2016. Employment outcomes include employment growth and the change in the employment rate for total employment. $\Delta Robots_{r,c}$ and $\Delta ICT_{r,c}$ are the explanatory variables of main interest and reflect the long-term change in regional robot and ICT exposure as defined in Equation 1 and Equation 2, respectively.[10]

The literature further discusses that international trade and the increasing integration of economies into global value chains have caused changes in employment and a restructuring of employment structures (e.g., Autor, Dorn, & Hanson, 2013; Dauth, Findeisen, & Suedekum, 2021). In this regard, the literature in particular underscores the role of an intensified trade with China. To account for such a labour market shock, I use, as proposed by the empirical literature, information about net exports vis-à-vis China for EU economies. Similar to robots and ICT, I construct the change in the regional trade exposure in the period 2001-2016 using trade data at the industry level and the regional employment data by industry of the base year 1995.

$\boldsymbol{X_{r,c}}$ denotes a vector containing additional explanatory variables that account for differences in the labour market and industry structure across regions. On the one hand, it includes information about the socio-demographic structure of the local labour force within regions: the employment shares of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. On the other hand, I add the employment share in manufacturing to proxy the local industry structure. All shares are introduced as initial values taken from 2001.

[9] Data limitations do not allow the consideration of even longer term dynamics.
[10] As a result of data limitations, the change in the regional ICT exposure captures dynamics between 2001 and 2015.

Finally, μ_c accounts for systematic country-specific differences, and the remaining $\epsilon_{r,c}$ represents the error term. Standard errors are clustered at the EU NUTS-1 level to allow for correlation among regions. The sample includes 98 EU NUTS-1 regions in 23 EU economies.[11]

The existing empirical literature also discusses important challenges that need to be taken into account to identify the effects of automation. Most importantly, employment and automation alike may be affected by unobserved shocks and developments that generate a spurious relationship between the two variables. Even though Specification 3 includes covariates regarding the labour market and the industry structure in regions, and country-specific trends, it does not fully account for the potential endogeneity issue. Moreover, employment dynamics can also have an impact on investments in automation that results in reverse causality. To address these endogeneity concerns, I apply an instrumental variable approach (two-stage least squares regression), as introduced by Acemoglu and Restrepo (2018). In doing so, information about automation in other high-income countries is deployed as an instrument on the grounds that countries face similar trends in technological progress but can experience different domestic local shocks with limited repercussions on investments in automation and labour market outcomes in other countries (Acemoglu & Restrepo, 2018; Dauth et al., 2021; Dottori, 2021).

Previous empirical studies on individual European countries draw on information from other European countries (Dauth et al., 2021; Dottori, 2021). As this analysis relies on an EU-wide sample of regions, I use information about automation from the United States, Japan and South Korea, to construct instruments for local exposure to automation (for a similar approach see Anton et al., 2020). In practise, the industry-level information about industrial robots and ICT capital stocks in the reference countries is allocated to European regions using the regional industry-level employment data of the European economies. In order to further mitigate simultaneity concerns, some empirical studies use regional industry-level employment data from years prior the period used to construct the initial local exposure to industrial robots and ICT (e.g., Acemoglu & Restrepo, 2018; Dauth et al., 2021; Dottori, 2021). As the harmonised regional employment data by industry are available only from 1995 onwards, I cannot apply data prior to this period to construct the instruments for the local automation exposure (for a similar limitation, see Anton et al., 2020; Chiacchio et al., 2018). Thus, the instruments are also constructed based on regional industry-level employment data from 1995.

In addition to the effects on total employment, this analysis also investigates heterogeneous effects across local industries. In a first step, we look at different employment effects of automation in manufacturing and non-manufacturing industries. The rich dataset further allows us to explore to what extent the total robot and ICT exposure in regions has an impact on employment in particular local industries (see Kariel, 2021, for a similar approach). This approach allows us to draw more detailed conclusions on replacement and productivity effects of automation.

[11] The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia, but includes regions from the United Kingdom.

4 Descriptive overview

In order to provide first insights into the local exposure to automation and its effects on employment, we look at the spatial dispersion of the dynamics in the local robot and ICT exposure in Figure 1.

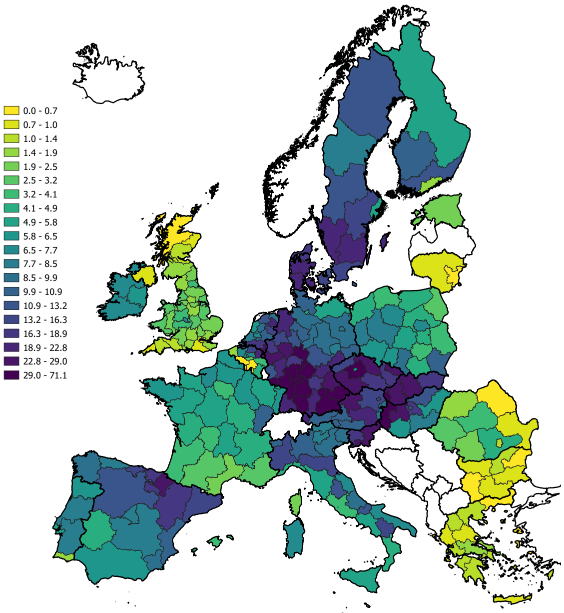
Figure 1a illustrates the change in the local robot exposure in EU NUTS-2 regions (including the NUTS-2 regions of the UK) calculated according to Equation 1. As can be seen, the local exposure varies across countries. For instance, we find a generally low level in Romania, Bulgaria, and Greece, but also in the UK; while regions with a large increase in robot exposure can be found in Germany, Czechia, Slovakia, and Sweden. Interestingly, regions with a large robot exposure tend to be spatially concentrated in central European countries. Importantly, within these countries we find interesting differences across regions. As robot adoptions is concentrated in the manufacturing industries, spatial patterns within countries also reflect differences in the industry structure across regions. The highest robot exposure can be found in the automotive industry-intensive regions of Germany, but also in Czechia (Střední Čechy) and Slovakia (Bratislava region). The spatial clusters that can be observed in the south and west of Germany and in the north of Italy are consistent with the geographic patterns for the robot exposure presented by Dauth et al. (2021) and Dottori (2021).

The other three maps in Figure 1 relate to the change in the local ICT exposure. In general, ICT capital stocks are much less concentrated in manufacturing industries than is the case for robot adoptions, and also show large dynamics in service industries. Figure 1b shows the change in the local IT exposure across EU NUTS-2 regions (including the NUTS-2 regions of the UK). Overall, we find relatively large general differences between the countries. Importantly, the local IT exposure ranges from negative to positive changes. These patterns indicate large general differences in investments in computer hardware across countries. As can be seen, the UK and Germany reveal predominantly negative changes in the local IT exposure. Accordingly, those countries had already invested in large IT capital stocks before 2001 and scaled back IT investments in the period 2001-2015. In contrast, countries such as Ireland, Czechia, the Netherlands and Finland show positive changes in all their NUTS-2 regions. In particular, Ireland registered a strong increase in local IT exposure, resulting from considerable investments in industry J (information and communication). However, given these general differences across countries, we also observe within-country variation across regions. Figure B.2b in the Appendix provides a detailed look at the variation of the change in the local IT exposure by country. Country-specific patterns, but also within-country variation can also be found for the change in the local CT exposure in Figure 1c. Germany and Hungary are dominated by negative changes, while Ireland, Sweden, Belgium, Finland and Austria show regions with a strong increase in CT capital stocks. Again, the large dynamics in the exposure in Irish regions are the result of CT investments in industry J. The dynamics by country are illustrated in Figure B.2c in the Appendix. Finally, Figure 1d maps the changes in the local exposure devoted to software and databases across regions. Even though, country-specific differences are again clearly visible, we also observe a pronounced regional concentration for instance in Spain and France. In addition to Ireland, Swedish regions show a strong general increase in the local exposure (see also in Figure B.2d in the Appendix), again caused by large investments in industry J. Importantly, the econometric analysis applied in this study takes into account country-specific differences by incorporating country dummies. The correlation among the change in the three local ICT exposures, is the highest between IT and CT, at around 0.486.

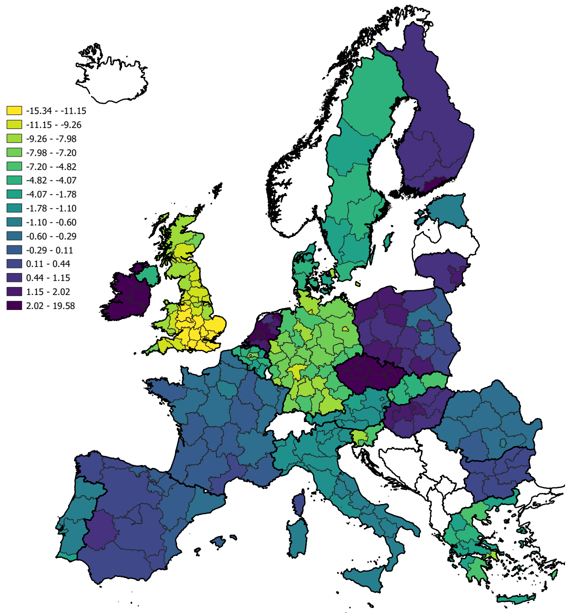
In order to provide a first insight into the relationship between automation and employment, we take a look at the unconditional correlation between the local exposure indicators and regional employment dynamics in Figure 2. Figure 2a shows the link between the local robot exposure and total employment growth between the period 2001 and 2016 in the NUTS-2 regions. As can be seen, total employment growth also varies to a large extent across regions. The regions with a relatively large decline in employment are clustered in Romania, while regions with a strong employment boost can be found in Poland, Hungary and the UK. Interestingly, we find a rather weak positive correlation between robot exposure and total employment growth.

Positive results for the correlation with total employment growth can also be found for the local CT exposure in Figure 2c and for the local exposure related to software and databases in Figure 2d. In contrast, the local IT exposure is the only indicator that reveals a weak negative correlation with total employment growth (see Figure 2b). Figure B.3 in the Appendix provides an overview of the results for the correlation with the change in the total employment rate. Importantly, this variable also accounts for changes in the regional working-age population. As can be seen, the correlation turns to negative when we consider the change in the employment rate for the local exposure related to CT, and software and databases, while it remains unchanged for robots and IT. As outlined in Section 3, in the econometric analysis, we additionally account for country-specific differences and for a set of region-specific covariates, and explore the effects on both the employment growth and the change in the employment rate.

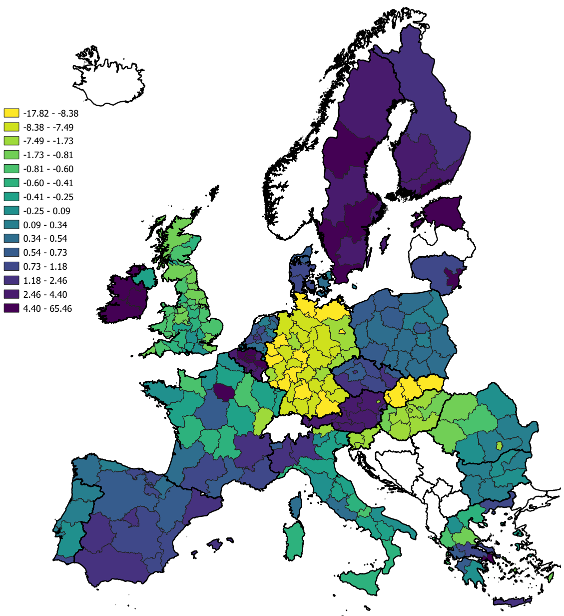
Figure 1 **Local exposure to automation**



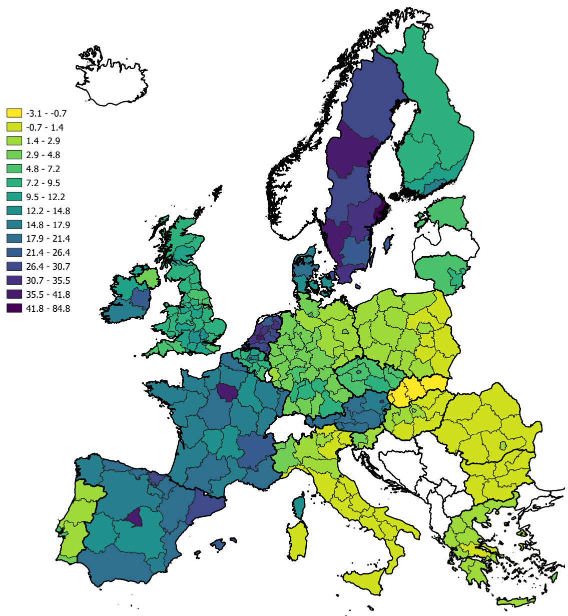
(a) **Change in local robot exposure**



(b) **Change in local IT exposure**



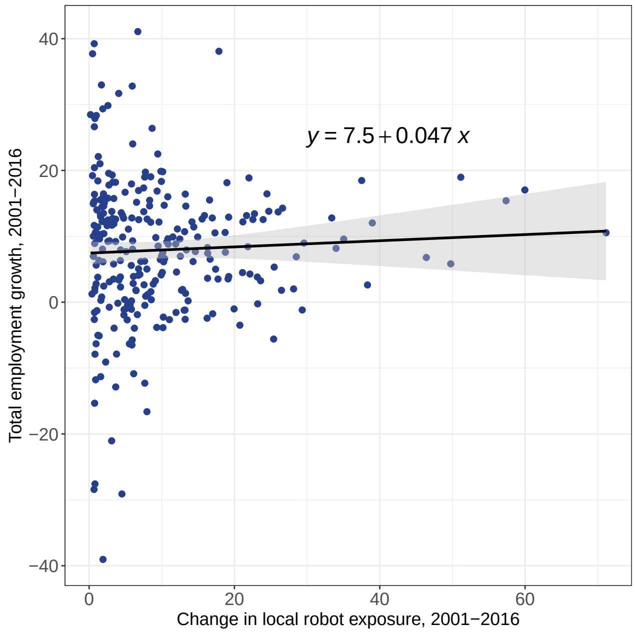
(c) **Change in local CT exposure**



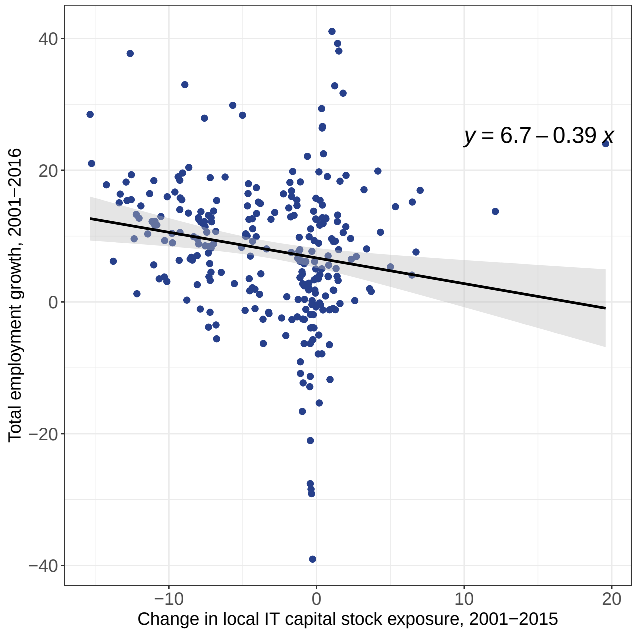
(d) **Change in local database & software exposure**

Source: IFR, EU-KLEMS, SBS employment data, ARDECO.
Notes: The figures illustrate the local exposure to robots and ICT across EU regions (including UK regions). The indicators are calculated based on Equation 1 and Equation 2. Figure *(a)* shows the local change in robots per 1,000 employed persons between 2001 and 2016; Figure *(b)* the local change in capital stock devoted to IT in 1,000 EUR per employed persons between 2001 and 2015; Figure *(c)* the local change in capital stock related to CT in 1,000 EUR per employed persons between 2001 and 2015; and Figure *(d)* the local change in capital stock related to software and database in 1,000 EUR per employed persons between 2001 and 2015. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. Own illustration.

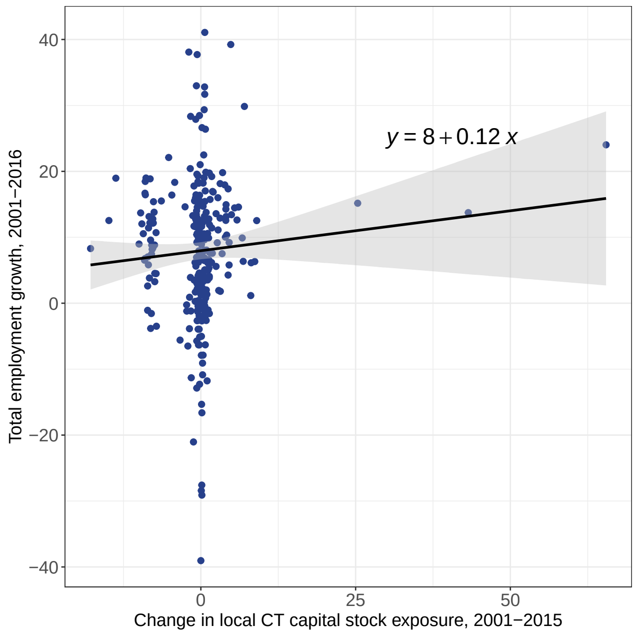
Figure 2 **Local exposure to automation and total employment growth**



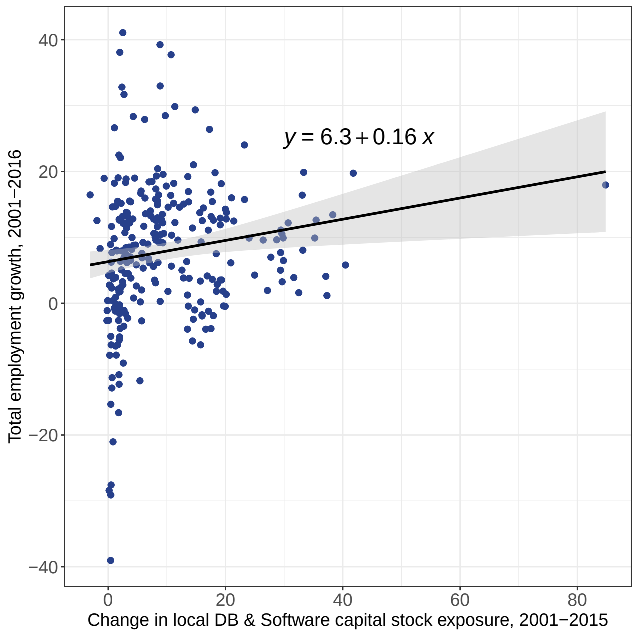
(a) **Change in local robot exposure**



(b) **Change in local IT exposure**



(c) **Change in local CT exposure**



(d) **Change in local database & software exposure**

Source: IFR, EU-KLEMS, SBS employment data, ARDECO.
Notes: The figures illustrate the unconditional correlation between the local exposure to robots and ICT across EU regions (including UK regions) and the local total employment growth. The automation indicators are calculated based on Equation 1 and Equation 2. Figure *(a)* shows the correlation for the local change in robots per 1,000 employed persons between 2001 and 2016; Figure *(b)* for the local change in capital stock devoted to IT in 1,000 EUR per employee between 2001 and 2015; Figure *(c)* for the local change in capital stock related to CT in 1,000 EUR per employee between 2001 and 2015; and Figure *(d)* for the local change in capital stock related to software and database in 1,000 EUR per employee between 2001 and 2015. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. Own illustration.

5 Results

In order to study in detail the effects of industrial robots and ICT on regional employment, I employ the econometric approach as discussed in Section 3. In a first step, I investigate the total equilibrium effect of automation at the local level on total employment as shown in Specification 3. In a further step, this analysis sheds light on heterogeneous employment effects across local industries.

As discussed in Section 3, by analysing the employment effects of automation, we need to take into account potential endogeneity. I apply an instrumental variable (IV) estimation to address this identification issue. In order to construct the instruments, I use industry-level information about the industrial robot stocks and ICT capital stocks in the US. In order to allocate these numbers to the regions covered in the sample of this analysis, I apply an approach similar to Equation 1 and Equation 2 based on regional industry-level employment data from 1995 for EU countries (including the UK). The instrument for the local robot exposure proves to be relevant. Overall, the regression results suggest an upward bias in the coefficients estimated without considering endogeneity, i.e. using an ordinary least squares (OLS estimation). This upward bias is consistent with the findings of Dottori (2021) for Italy. Anton et al. (2020) instead use information from South Korea to construct their instrument for the robot exposure. Using information from South Korea to construct our instrument produces similar results to those using US data.[12] In contrast, unfortunately, the instruments are less relevant for the change in the ICT exposure compared with the local robot exposure. To construct the instrument, I again use information from the US and alternatively also information from Japan. Overall, the estimated coefficients using the IV estimation, however, tend to be close to those using OLS. Therefore, I do not apply the IV approach for the exposures to ICT investments in the results presented below.

5.1 Total employment effects

First, we look at the total local effects for total employment dynamics in Table 1. The first panel reports the estimated effects of industrial robots and the three ICT items on employment growth, while the second panel lists the estimated effects on the change in the employment rate in 2001-2016. In all specifications, I include country-fixed effects and a set of local covariates, such as the employment share in manufacturing, and the employment share of females, individuals older than 54 years, foreign-born, and medium- and highly educated individuals. In the first two columns of each panel, the specification additionally includes either the robot exposure or the ICT exposures. The third columns ((3) and (7)) show the results for controlling for the robot and the ICT exposure simultaneously. Finally, the last specifications of each panel add the local exposure to Chinese net exports.

The first result in Table 1 shows the estimated employment effects for the robot exposure. This variable is instrumented with the change in the robot exposure, using information about US robot stocks. The test statistics in the last row in Table 1 are sufficiently large to suggest that the instruments are not weak. Interestingly, the estimated coefficients are not statistically different from zero in all specifications. This indicates that robot adoption in European regions does not seem to have had an impact on total employment dynamics. This finding stands in contrast to the results of Anton et al. (2020) and Chiacchio et al. (2018). Both studies find negative longer term employment effects for the

[12] I also estimated specifications in which I used both the instrument based on US data and the instrument based on data from South Korea. The overidentification test indicated no rejection of the null hypothesis (insignificant *Hansen J statistic*). Accordingly, the instruments seem to be valid.

Table 1 **Effects of automation on total employment in EU regions, 2001-2016**

Dependent variable:	*Employment growth, 2001-2016*				*Change in employment rate, 2001-2016*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Robots$	0.0595	-	0.0831	0.0835	-0.0237	-	0.000904	0.00102
	(0.134)	(-)	(0.138)	(0.139)	(0.0962)	(-)	(0.0975)	(0.0979)
ΔIT	-	0.513	0.543	0.562	-	-0.241	-0.240	-0.235
	(-)	(0.429)	(0.415)	(0.411)	(-)	(0.374)	(0.357)	(0.356)
ΔCT	-	-0.188	-0.188	-0.195	-	-0.0911	-0.0911	-0.0931
	(-)	(0.253)	(0.233)	(0.236)	(-)	(0.205)	(0.192)	(0.193)
$\Delta Software\&Database$	-	0.0337	0.0301	0.0242	-	-0.193**	-0.193***	-0.195***
	(-)	(0.0898)	(0.0851)	(0.0866)	(-)	(0.0757)	(0.0710)	(0.0713)
Observations	270	270	270	270	270	270	270	270
Manufacturing share	Y	Y	Y	Y	Y	Y	Y	Y
Socio-demographic controls	Y	Y	Y	Y	Y	Y	Y	Y
$\Delta TradeChina$	N	N	N	Y	N	N	N	Y
Country-FE	Y	Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap test statistics	14.15	-	14.05	14.21	14.15	-	14.05	14.21

Notes: Standard errors in parentheses are clustered by 98 NUTS-1 regions. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on the US robot stocks. ΔIT, ΔCT and $\Delta Software\&Database$ capture the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. * p<0.1, ** p<0.05, *** p<0.01.

robot exposure based on sub-samples of EU regions, which suggests that robots replace workers and eventually reduce the total number of jobs. In contrast, the insignificant effect is consistent with the results found by Dauth et al. (2019) for Germany and Dottori (2021) for Italy. The use of industrial robots does not go hand in hand with an overall decline in the number of jobs.

Next, we turn to the results for the local exposures to ICT investments. Importantly, similarly to robots, the estimates for IT and CT do not suggest an impact on total employment. Chiacchio et al. (2018) find evidence for positive employment effects for IT investments. We only observe positive estimated coefficients for IT on employment growth, although none of these estimates is statistically significant. In contrast, investments in software and databases are shown to have had an effect on the total employment, although only in relation to the change in the employment rate. The estimated coefficient suggests that an increase in investments by 1,000 EUR per employed persons reduces the employment rate by 0.195 percentage points, on average. However, the effect is not indicated by the result for employment growth. For this employment outcome, we find a positive estimated effect, which is not statistically different from zero. Accordingly, the results point to relatively weak effects of automation on regional total employment dynamics.

5.2 Employment effects in manufacturing and non-manufacturing industries

In a next step, we explore the employment effects of automation in manufacturing industries and all other non-manufacturing industries separately. Manufacturing industries are considerably more exposed to robots than in the case for other industries, while non-manufacturing industries are characterised by a comparatively large proportion of ICT capital stocks (see Figure B.1 in the Appendix). Against this backdrop, the impact may differ between manufacturing and non-manufacturing industries.

The specification I estimate includes the same set of covariates as in the baseline specification, but applies employment dynamics in manufacturing and non-manufacturing industries separately as the dependent variable. The change in the automation exposures, therefore, takes into account again the total stocks of industrial robots and ICT capital. For this reason, the estimates can again be understood as full equilibrium effects that account for the direct and also spillover effects of automation on regional employment. Dauth et al. (2021) argue that the displacement effect of industrial robots should be primarily evident in the robot-intensive manufacturing industry, while productivity and spillover effects should be more pronounced in the non-manufacturing industries.

Table 2 presents the estimated employment effects of automation for the manufacturing industry. As with Table 1, the left panel reports the results for employment growth and the right panel those for the change in the employment rate. The change in the local robot exposure shows a consistent negative effect in all specifications. Importantly, the results are statistically different from zero, although only weakly for employment growth. These total effects suggest that the use of robots has replaced human labour and thus has reduced on average the number of manufacturing jobs in EU regions. On average, one additional industrial robot per 1,000 employed persons decreases the employment rate in the manufacturing industry by 0.127 percentage points. For the local change in IT capital stock, we find predominantly positive estimated coefficients, but the effects are statistically significant only for employment growth. Accordingly, IT investments tend to have been associated with an increase of manufacturing jobs in EU regions. In contrast, the estimates for CT reveal varying signs for employment growth and the change in employment rate. None of these estimates is statistically significant. Consistent with the results for total employment, investment in software and databases indicates a negative impact on employment in manufacturing industry. Importantly, we find a negative statistically significant impact on both employment growth and the change in the employment rate.

Table 2 **Effects of automation on manufacturing employment in EU regions, 2001-2016**

Dependent variable:	*Employment growth, 2001-2016*				*Change in employment rate, 2001-2016*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Robots$	-0.866*	-	-0.761*	-0.766*	-0.127**	-	-0.126**	-0.127**
	(0.463)	(-)	(0.446)	(0.454)	(0.0531)	(-)	(0.0525)	(0.0527)
ΔIT	-	2.165***	1.887**	1.685**	-	0.0714	0.0252	0.00408
	(-)	(0.795)	(0.782)	(0.680)	(-)	(0.0755)	(0.0808)	(0.0685)
ΔCT	-	-0.198	-0.200	-0.127	-	0.0564	0.0561	0.0637
	(-)	(0.401)	(0.327)	(0.318)	(-)	(0.0590)	(0.0452)	(0.0450)
$\Delta Software\&Database$	-	-0.529**	-0.497**	-0.433**	-	-0.0526**	-0.0472**	-0.0405**
	(-)	(0.239)	(0.202)	(0.184)	(-)	(0.0261)	(0.0198)	(0.0190)
Observations	270	270	270	270	270	270	270	270
Manufacturing share	Y	Y	Y	Y	Y	Y	Y	Y
Socio-demographic controls	Y	Y	Y	Y	Y	Y	Y	Y
$\Delta TradeChina$	N	N	N	Y	N	N	N	Y
Country-FE	Y	Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap Wald statistics	14.15	-	14.05	14.21	14.15	-	14.05	14.21

Notes: Standard errors in parentheses are clustered by 98 NUTS-1 regions. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on the US robot stocks. ΔIT, ΔCT and $\Delta Software\&Database$ capture the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. * p<0.1, ** p<0.05, *** p<0.01.

Next, we take a look at the employment effect of automation in non-manufacturing industries in Table 3. In contrast to the results for the manufacturing industry, the change in the robot exposure shows a positive sign in all specifications. However, the results are only weakly statistically significant for employment growth. When I instrument the robot exposure with information about robot stocks from South Korea instead of the US, the positive effects become more significant (see Table B.1 in the Appendix). Thus, robot adoption in EU regions tends to increase employment in non-manufacturing industries, on average. This suggests that the robot-induced productivity effects play an important role for employment in the robot-non-intensive non-manufacturing industries. Interestingly, even though ICT investments are more pronounced in non-manufacturing industries (see Figure B.1), the local IT and CT exposure do not show any statistically significant result. In contrast, in accordance with the findings for total employment, the local exposure to software and databases has reduced, on average, the employment rate in non-manufacturing industries.

Table 3 **Effects of automation on non-manufacturing employment in EU regions, 2001-2016**

Dependent variable:	*Employment growth, 2001-2016*				*Change in employment rate, 2001-2016*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Robots$	0.289*	-	0.316*	0.317*	0.103	-	0.127	0.128
	(0.164)	(-)	(0.172)	(0.176)	(0.105)	(-)	(0.110)	(0.111)
ΔIT	-	0.442	0.557	0.620	-	-0.312	-0.266	-0.239
	(-)	(0.519)	(0.516)	(0.490)	(-)	(0.380)	(0.365)	(0.356)
ΔCT	-	-0.291	-0.290	-0.313	-	-0.148	-0.147	-0.157
	(-)	(0.343)	(0.304)	(0.308)	(-)	(0.241)	(0.215)	(0.217)
$\Delta Software\&Database$	-	0.108	0.0943	0.0744	-	-0.140**	-0.146**	-0.154**
	(-)	(0.109)	(0.0975)	(0.0980)	(-)	(0.0652)	(0.0649)	(0.0661)
Observations	270	270	270	270	270	270	270	270
Manufacturing share	Y	Y	Y	Y	Y	Y	Y	Y
Socio-demographic controls	Y	Y	Y	Y	Y	Y	Y	Y
$\Delta TradeChina$	N	N	N	Y	N	N	N	Y
Country-FE	Y	Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap Wald statistics	14.15	-	14.05	14.21	14.15	-	14.05	14.21

Notes: Standard errors in parentheses are clustered by 98 NUTS-1 regions. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on the US robot stocks. ΔIT, ΔCT and $\Delta Software\&Database$ capture the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. * p<0.1, ** p<0.05, *** p<0.01.

The comparison between the results for manufacturing (see Table 2) and non-manufacturing industries (see Table 3) points to a number of interesting findings. First, the results suggest a varying effect of robots across industries. The replacement effect captures the substitution of human labour by adopting technological advances in the production process. Given the negative employment effects for local manufacturing industries, the replacement effect seems to outweigh the robot-induced productivity effects with their positive repercussions for manufacturing employment. I have also estimated a specification in which I included the change in the regional gross value added at constant prices (taken from the ARDECO database) between 2001 and 2016 to account for productivity gains in the EU regions. The results indicate that productivity effects indeed counteract the replacement effect. By controlling for productivity gains, the negative effect for the local robot exposure becomes larger. In contrast, positive employment spillovers seem to predominate in non-manufacturing industries, as local employment in those industries tends to have gained from a more intensive use of robots mainly in manufacturing industry. Interestingly, the job losses in manufacturing seem to be offset by employment increases outside manufacturing, as we fail to find an impact on total employment. This finding is in line with the results of Dauth et al. (2021) for Germany. Moreover, the fact that the negative employment effects caused by the robot adoption operate exclusively in the local manufacturing industry is also supported by the results of Dottori (2021) for Italy. Second, investments in IT and CT capital stocks do not seem to have a large impact on local employment, either in the manufacturing industry or in non-manufacturing industries. We only find an indication of a positive employment effect for the local IT exposure in the local manufacturing industry. Third, however, the results indicate a negative employment effect emanating from the local exposure to software and databases. This effect operates in both manufacturing and non-manufacturing industries and is therefore also visible for total employment.

5.3 Heterogeneity within manufacturing and service industry

The results presented above indicate varying employment effects of automation, in particular of industrial robots, in manufacturing and non-manufacturing industries. In the next step, I explore heterogeneous equilibrium effects on employment within those industry groups (see Kariel, 2021, for a similar approach for the UK). This approach allows us to identify the most affected industries at a rather granular level. For instance, Dauth et al. (2021) argue that positive employment spillover effects of industrial robots operate predominantly in service industries. In addition, the automotive industry, in particular, is exposed to industrial robots, which also suggests stronger operating effects in this industry. Importantly, the constructed harmonised regional employment data allow us to shed light on regional industry-specific employment dynamics. Similar to the specifications estimated above, the set of covariates is the same as applied in the baseline specification.

First, we take a look at the results for individual manufacturing industries. Figure 3 plots the estimated effect of industrial robots and ICT on employment growth in nine different manufacturing industry groups. I distinguish between the industries *food, beverages and tobacco* (C10-C12); *textiles, apparel and leather* (C13-C15); *wood, paper and printing* (C16-C18); *petroleum, chemicals, pharmaceutical, plastic, and non-metallic mineral products* (C19-C23); *basic metals and fabricated metal products* (C24-C25); *computer, electronic products and electrical equipment* (C26-C27); *machinery* (C28); *motor vehicles and other transport* (C29-C30); and, *furniture and other manufacturing* (C31-C33). The bars indicate the estimated coefficient, while the whiskers illustrate the corresponding 90% confidence interval. The regression results for regional employment growth and for the change in the local employment rate are reported in Table B.2 and Table B.3 in the Appendix, respectively. Figure 3a illustrates the estimated effects of industrial robots on employment growth across manufacturing industries. As can be seen, almost all industries show a negative estimated coefficient. However, the estimates are only statistically different from zero in the industries *motor vehicles and other transport*; *computer, electronic products and electrical equipment*; and *petroleum, chemicals, pharmaceutical, plastic, and non-metallic mineral products*. The results suggest that the replacement effects of robots dominates over the robots-induced productivity effects, in particular, in the industries *motor vehicles and other transport*; but also in the industries *computer, electronic products and electrical equipment*.

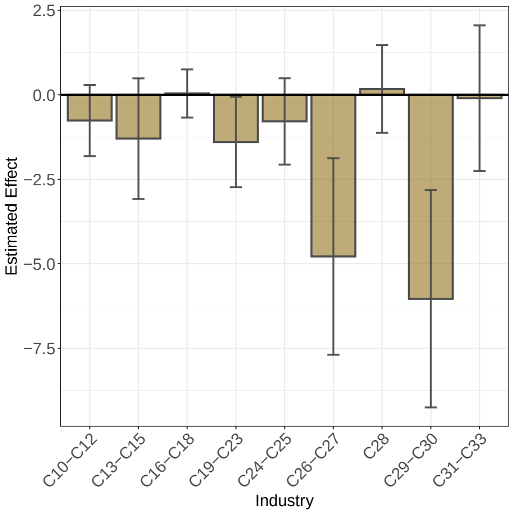
Next, Figure 3b shows the effects for the local IT exposure. Most of the estimates suggest a positive impact on the local employment growth. We find statistically significant results in the industries *food, beverages and tobacco*; *wood, paper and printing*; and *basic metals and fabricated metal products*. In contrast, the industry *motor vehicles and other transport* shows a negative statistically significant effect. As indicated by Figure 3c, the local CT exposure does not show a pattern in the estimated coefficients. With the exception of the industry *furniture and other manufacturing*, none of the estimates is statistically different from zero. The local exposure to software and databases, however, reveals a clear pattern of negative estimated coefficients (see Figure 3d). Importantly, nearly all estimates are statistically significant. Accordingly, the negative impact of the local change in software and database investments is relatively balanced across manufacturing industries.

In a further step, I estimate the effects of industrial robots and ICT in individual service industries in

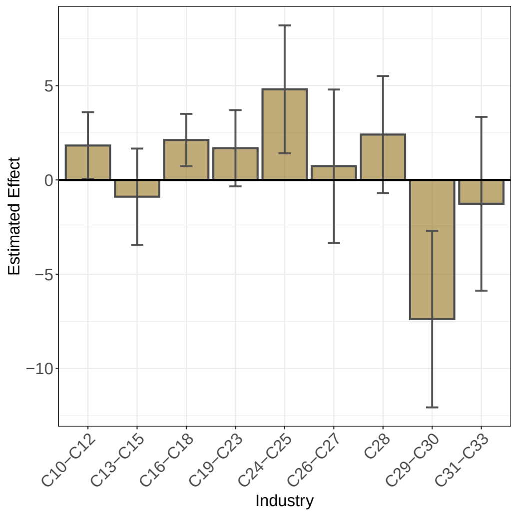
Figure 4. I distinguish between *wholesale and retail, transportation and storage, and accommodation and food service activities* (G-I); *financial and insurance, and real estate activities* (K-L); *professional and scientific activities, administrative and support services* (M-N); and *public administration, education, arts, entertainment, and other services* (O-U).

Contrary to the results for industrial robots in Figure 3, we find predominantly positive estimated coefficients that are statistically different from zero in the industries G-I and M-N. These results suggest that positive employment spillovers operate at a large scale in those service industries, as most industrial robots have been deployed in the manufacturing industries. In line with the results for the manufacturing industries, we also find evidence for statistically significant positive and negative employment effects for the IT exposure in Figure 4b. In contrast, for the CT exposure in Figure 4c, we do not observe any significant results. Furthermore, in accordance with previous findings, the statistically significant result for the local exposure to software and databases in Figure 4d is characterised by a negative sign.

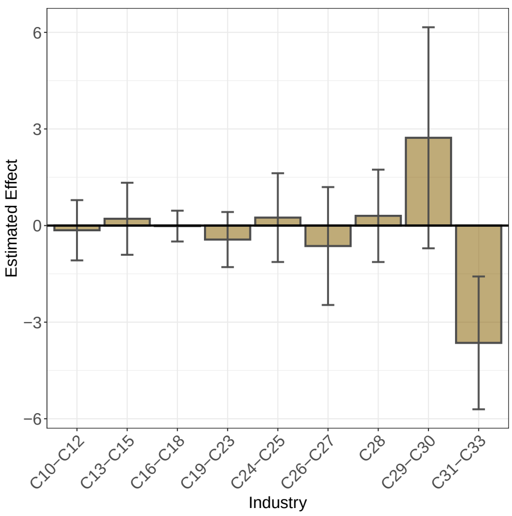
Figure 3 **Estimated effects of automation on employment growth in manufacturing industries**



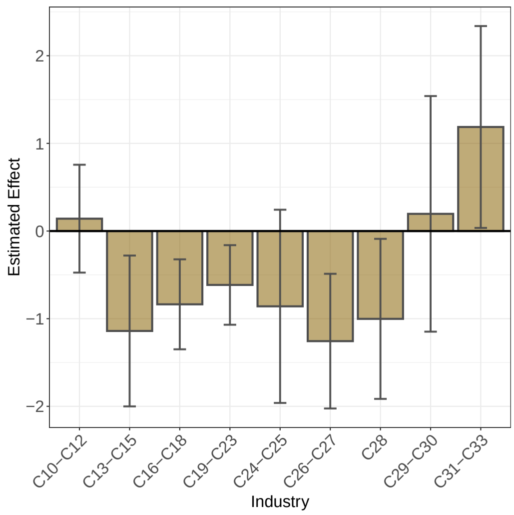
(a) **Effects of change in robot exposure**



(b) **Effects of change in IT exposure**



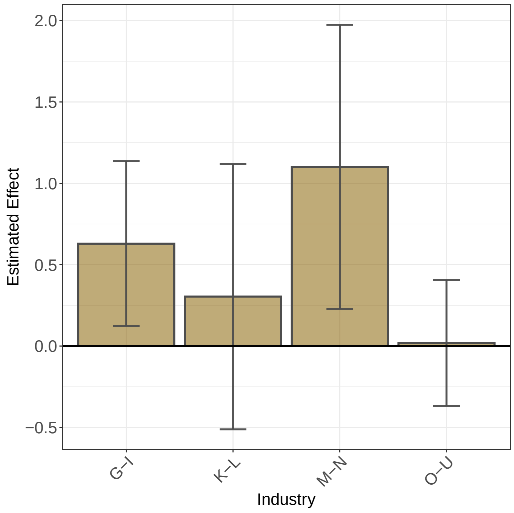
(c) **Effects of change in CT exposure**



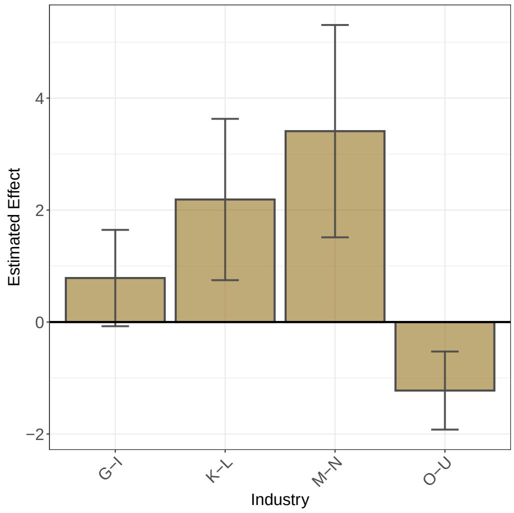
(d) **Effects of change in database & software exposure**

Source: IFR, EU-KLEMS, SBS employment data, ARDECO.
Notes: The bars indicate the estimated coefficient of the automation measures on the employment growth in individual industries, while the whiskers illustrate the corresponding 90% confidence interval. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on the US robot stocks. ΔIT, ΔCT and $\Delta Software\&Database$ capture the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net-exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. * p<0.1, ** p<0.05, *** p<0.01. *Food, beverages and tobacco* (C10-C12); *textiles, apparel and leather* (C13-C15); *wood, paper and printing* (C16-C18); *petroleum, chemicals, pharmaceutical, plastic, and non-metallic mineral products* (C19-C23); *basic metals and fabricated metal products* (C24-C25); *computer, electronic products and electrical equipment* (C26-C27); *machinery* (C28); *motor vehicles and other transport* (C29-C30); and, *furniture and other manufacturing* (C31-C33). Own illustration.

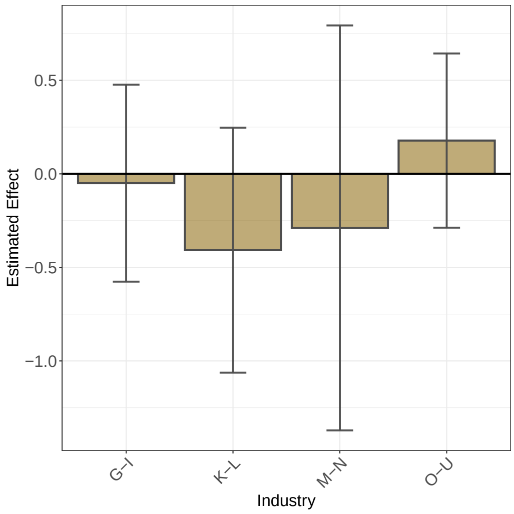
Figure 4 **Estimated effects of automation on employment growth in individual service industries**



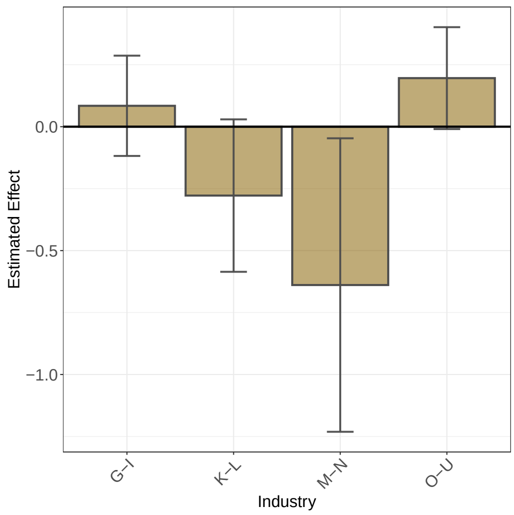
(a) **Effects of change in robot exposure**



(b) **Effects of change in IT exposure**



(c) **Effects of change in CT exposure**



(d) **Effects of change in database & software exposure**

Source: IFR, EU-KLEMS, SBS employment data, ARDECO.
Notes: The bars indicate the estimated coefficient of the automation measures on the employment growth in individual industries, while the whiskers illustrate the corresponding 90% confidence interval. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on the US robot stocks. ΔIT, ΔCT and $\Delta Software\&Database$ capture the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. * p<0.1, ** p<0.05, *** p<0.01. *Wholesale and retail, transportation and storage, and accommodation and food service activities* (G-I); *financial and insurance, and real estate activities* (K-L); *professional and scientific activities, administrative and support services* (M-N); and *public administration, education, arts, entertainment, and other services* (O-U). Own illustration.

6 Robustness checks

In order to test the robustness of the results discussed above, I estimate a set of additional specifications. Specifically, I consider further explanatory variables, exclude regions from the sample and use weights in the estimations. Detailed regression results are available upon request.

Additional explanatory variables. In the specifications estimated and discussed above, I include covariates regarding the region-specific socio-demographic employment structure and the employment share in manufacturing. This set is consistent with that applied by Dauth et al. (2021) and Dottori (2021). Other empirical analyses, however, introduce other explanatory variables (e.g., Acemoglu & Restrepo, 2019; Kariel, 2021). I therefore estimate specifications that consider further covariates. To account for agglomeration effects, I add the initial population density and population to the set of explanatory variables. Furthermore, I include initial employment shares in manufacturing, distinguishing between *high-tech*, *mid-high-tech*, *mid-low-tech*, and *low-tech* industries.[13] The estimated effects of these additional specifications are in line with the baseline results.
Moreover, the covariates of the baseline specification are introduced as initial values from 2001. Dauth et al. (2021) argue for using initial values in order to avoid endogeneity issues. However, Anton et al. (2020) also use changes of the covariates as a robustness check. I also estimate a specification that accounts for dynamics in the socio-demographic employment structure over the period 2001-2016. The estimated effects are revealed to be robust.

Excluding Germany. Dauth et al. (2021) provide evidence for Germany that negative displacement effects of industrial robots operate predominantly in the local manufacturing industry, but positive productivity and spillover effects are evident in local non-manufacturing industries. As the findings of this study point to similar diverse impacts of industrial robots, I re-estimate the baseline specifications without Germany. The exclusion of German regions does not alter the estimated effects.

Excluding outliers. The graphs presented and discussed above have already indicated some outliers in the main variables applied in this study. I re-estimated the specification by excluding regions that represent outliers. In general, the estimated effects are shown to be in line with the baseline results. The estimates for investment in software and databases lose some of their statistical significance. However, the heterogeneity analysis within the manufacturing and non-manufacturing industries reveals that the statistically significant estimated coefficients show a predominantly negative sign.

Weights-based estimations. I also re-estimate the baseline specifications using the initial working age population and the initial number of total employed individuals. The results for industrial robots again remain robust. However, the results for investment in software and databases prove statistically insignificant for total local manufacturing and non-manufacturing industry. Similar to the previous robustness check, the heterogeneity analysis within individual industries suggests negative effects.

Different time horizons. In the baseline specifications, I consider longer-term employment effects that operate over the time period 2001-2016. In order to examine the heterogeneity of the effects over time I also estimate the specifications by considering the time periods 2001-2008 and 2008-2016

[13] Definition is taken from Eurostat. *High-tech* covers *C21* and *C26*; *mid-high-tech C20*, *C27*, *C28*, *C29*, *C30*; *mid-low-tech C19*, *C22*, *C23*, *C24*, *C25*; and *low-tech C10-C12*, *C13-C15*, *C16*, *C17*, *C18*, *C31-C33*.

separately. Overall, the results do not indicate varying effects of automation on employment dynamics over time.

7 Conclusion

This paper analyses the effects of industrial robots and ICT on regional employment in EU countries. I combine business statistics and national accounts as well as regional accounts data to construct a harmonised regional industry-specific employment dataset. Based on these data, this study presents novel findings on the repercussions of automation and computerisation for employment in EU labour markets for the period 2001-2016. Specifically, this study uses detailed industry-level information about three ICT investment items (IT, CT, and software and databases) for EU countries. Furthermore, the detailed dataset also allows to provide insights for heterogeneous effects on employment across individual local industries.

The results suggest relatively weak employment effects of automation in EU regions. Industrial robots and IT and CT investments are shown to have no impact on the total number of jobs. Only investments in software and databases can be seen to have a negative effects on regional total employment dynamics.

However, the effects of automation differ between manufacturing and non-manufacturing industries. Industrial robots show negative employment effects in local manufacturing industries, but positive employment effects in local non-manufacturing industries. The replacement effect captures the substitution of human labour by adopting technological advances in the production process. Given the negative employment effects in the manufacturing industry, the negative replacement effect seems to dominate the positive robot-induced productivity effects in the manufacturing industry. However, positive employment spillovers seem to operate in non-manufacturing industries, as local employment in those industries tends to have gained from a more intensive use of robots mainly in manufacturing industry. Accordingly, the job losses in manufacturing seem to be offset by employment increases outside manufacturing, as we fail to find an effect on total employment.
The analysis of employment effects in individual industries further show that the negative total effect of industrial robots is concentrated in particular local manufacturing industries, while the positive total effect is pronounced in local service industries.

IT investments show positive employment effects only in local manufacturing industries, while CT investments prove to be irrelevant for employment dynamics in both local manufacturing and local non-manufacturing industry. In contrast, investments in software and databases indicate a predominantly negative impact on local employment. Interestingly, this negative effect operates in a relatively balanced way across manufacturing industries.

Taken together, the results suggest that automation does not replace workers or eventually reduce the total number of jobs in EU regions on a large scale. Only investments in software and databases appear, on average, to have reduced total employment, while IT investments are seen to be associated with positive productivity effects in manufacturing industries. In contrast, industrial robots reduce the number of jobs in robot-adopting industries, but produce positive employment effects in non-robot-adopting service industries. These results for industrial robots are different to those presented in previous studies on EU regions, but they are supportive of recent findings for individual EU countries (i.e. Germany and Italy) that rely on comprehensive administrative data. These diverging effects of industrial robots suggest important transitions in regional employment structures from manufacturing to service employment. Ongoing technological and automation (e.g. AI) advances may produce similar effects on employment (Acemoglu & Restrepo, 2019) and may therefore intensify these transitions. Thus, it is important that labour market institutions actively mediate these structural shifts in regional employment structures (Dauth et al., 2021).

This analysis has used a harmonised regional industry-level employment dataset covering 270 EU NUTS-2 regions (including NUTS-2 regions of the UK). However, this dataset possesses shortcomings. As a result of data limitations, only 1-digit industry-level employment information in local non-manufacturing industries can be used. As ICT investments are pronounced in non-manufacturing industries, this limitation has repercussions for the related estimated employment effects. Thus, the availability of regional employment data at a more detailed industry level in non-manufacturing industries would enable more reliable insights, in particular into the effects of ICT investments on regional employment.

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A Appendix – Data preparation

A.1 Imputation of ICT data

In this study, I use information about ICT capital stocks related to computer hardware (IT), telecommunication equipment (CT), and computer software and databases (Software & Database), taken from EU-KLEMS and from the European System of National Accounts (ESA) provided by Eurostat. As discussed in Section 2, Bulgaria, Hungary, Ireland, Poland, Portugal, Slovenia and Lithuania lack detailed information.[14] In order to have information available for all EU countries, reference countries are selected for imputing the missing data (see Table A.1).

Table A.1 **List of countries with missing ICT data and reference countries applied for imputation**

Country with missing data	Reference countries
Bulgaria	Greece, Slovakia
Estonia	Finland, Latvia
Hungary	Austria, Czechia
Ireland	United Kingdom, Netherlands
Poland	Czechia, Slovakia
Portugal	Spain, France
Slovenia	Slovakia, Austria
Lithuania	Finland
Romania	Greece, Slovakia

Note: As reference countries typically neighbouring countries have been chosen or countries where there is reason to believe that they share important structural features (e.g. a high share of headquarters of foreign multinational enterprises.

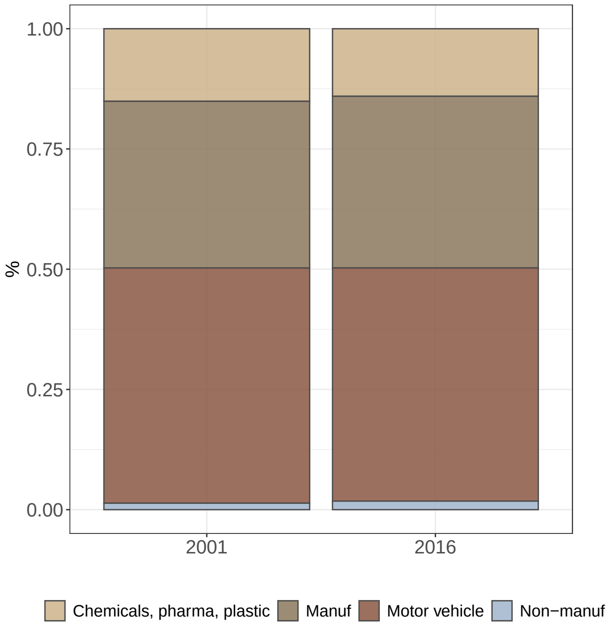
Source: Own illustration.

Countries with missing detailed industry-level information about ICT capital stocks report information only at the economy level or at NACE 1-digit divisions. To obtain ICT capital stocks at a more detailed industry level, imputations are based on capital intensities by detailed industries. In doing so, the capital intensity of the reference countries is calculated by dividing detailed industry-level capital stock of the respective asset type by detailed industry-level gross output, using data from the World-Input-Output Database (WIOD). These intensities are then adopted for the country with the missing data. In the countries with missing data, the industry-level capital intensities of the reference countries are multiplied with the industry-level gross output of the country with missing data (also extracted from the WIOD). In a further step, these raw imputed ICT capital stock data are compared with the initially available aggregated ICT capital stocks in the missing countries. Accordingly, the imputed industry-level capital stocks are rescaled such that the sum of the imputed values equals the reported economy-level capital stocks or the sum of sub-sector totals.

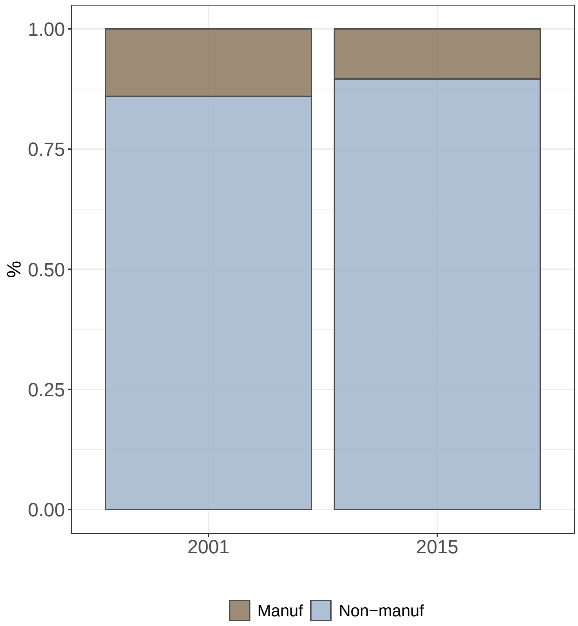
[14] In addition, Denmark does not report information about the capital stock in relation to computer software and databases. These data are also imputed.

B Appendix – Additional graphs and tables

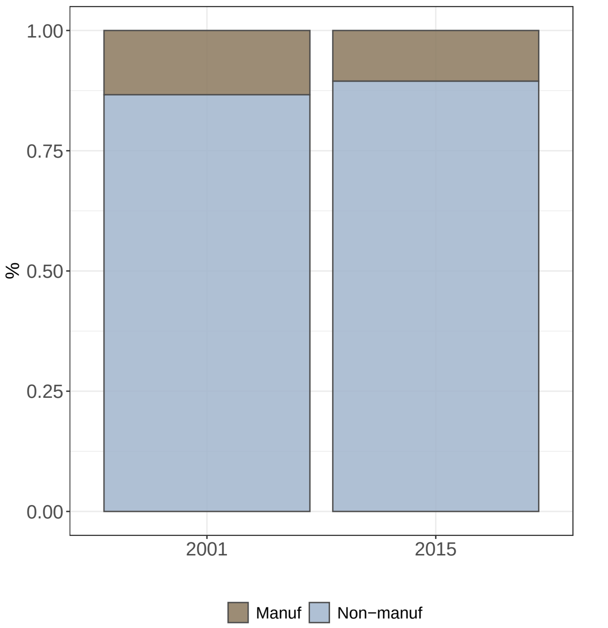
Figure B.1 **Distribution across industries**



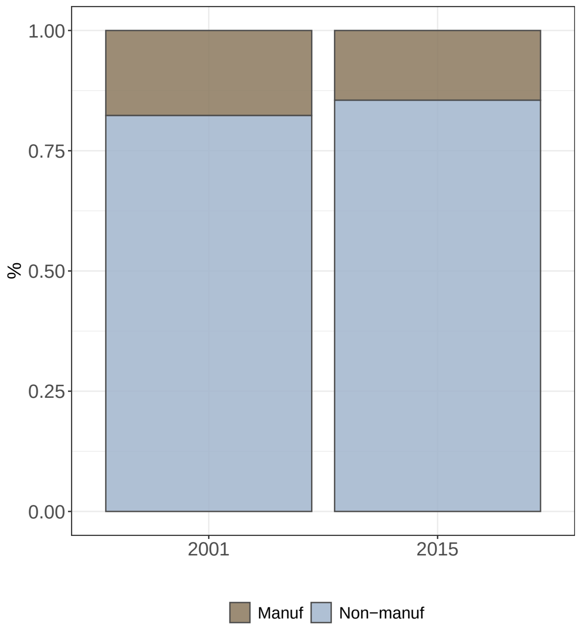
(a) **Stocks of robots**



(b) **IT capital stocks**



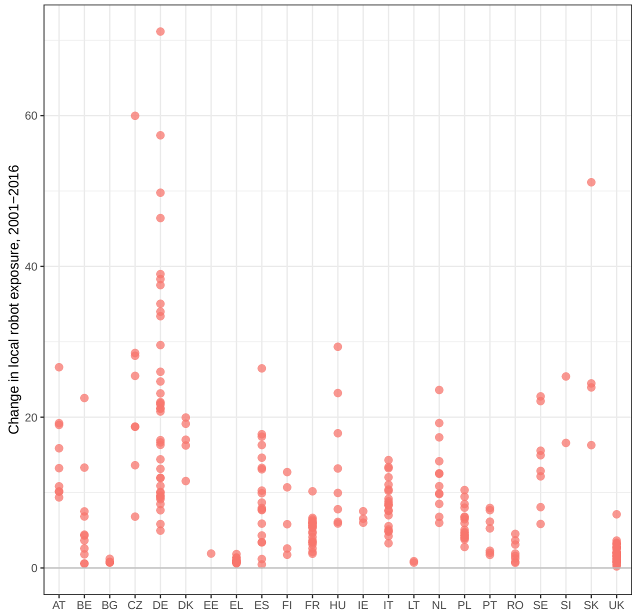
(c) **CT capital stocks**



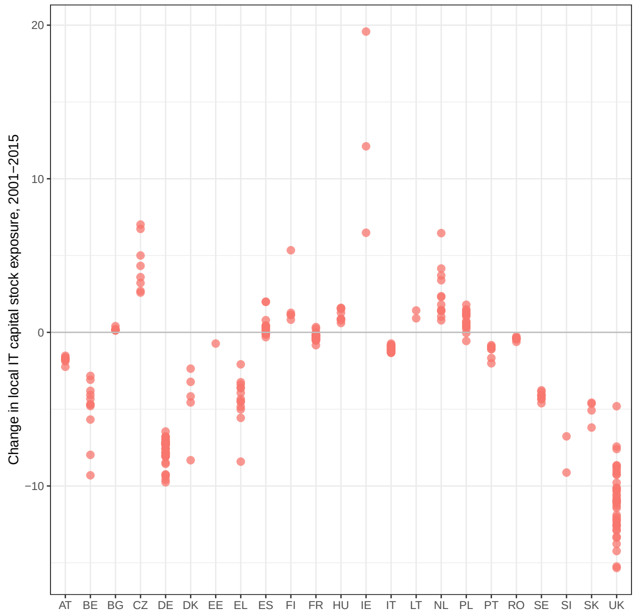
(d) **Software & database capital stocks**

Source: IFR, EU-KLEMS, SBS employment data, ARDECO.
Notes: The figures show the distribution across industries of robots and ICT capital in 2001 and 2015/2016. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. Own illustration.

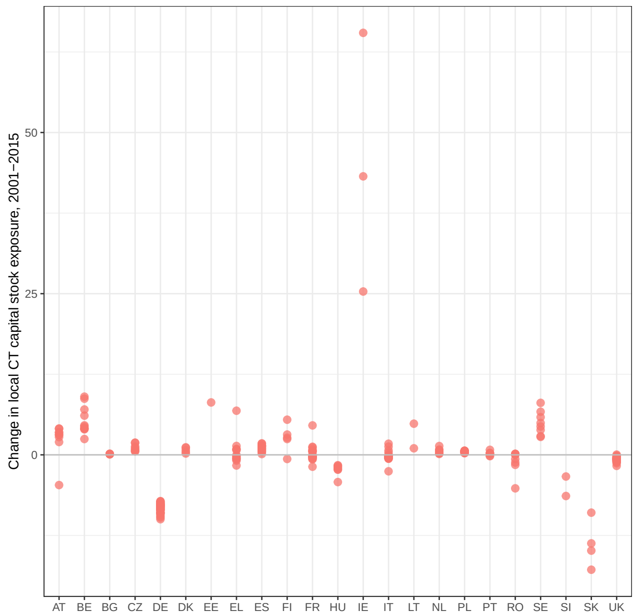
Figure B.2 **Variation in local exposure within countries**



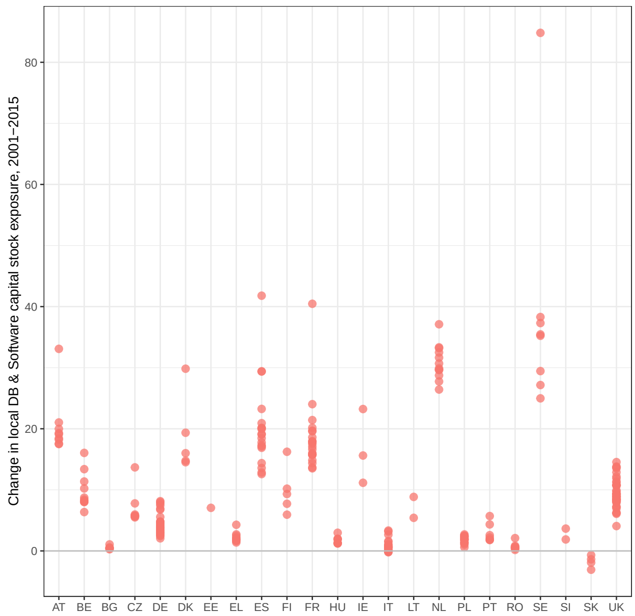
(a) **Change in local robot exposure**



(b) **Change in local IT exposure**



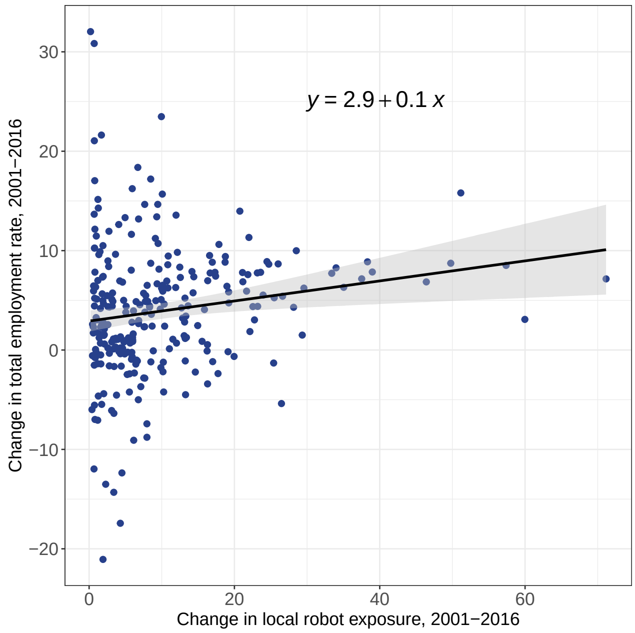
(c) **Change in local CT exposure**



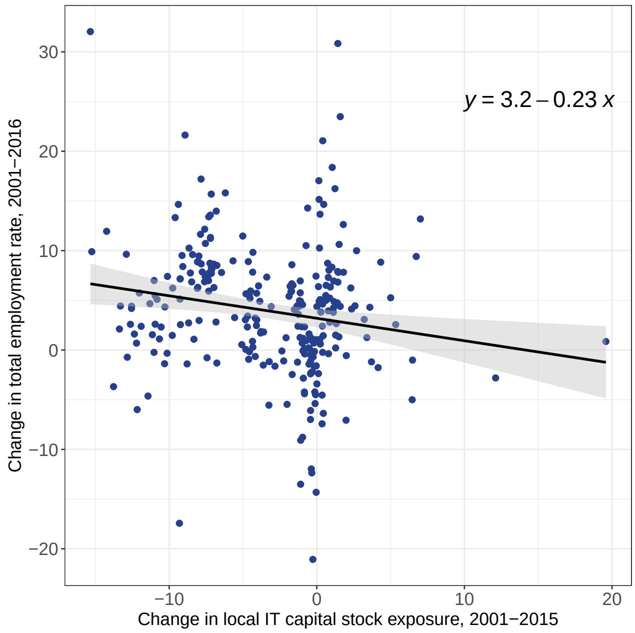
(d) **Change in local database & software exposure**

Source: IFR, EU-KLEMS, SBS employment data, ARDECO.
Notes: The figures illustrate the variation of local exposure to robots and ICT across regions within countries. The indicators are calculated based on Equation 1 and Equation 2. Figure *(a)* shows the local change in robots per 1,000 employed persons between 2001 and 2016; Figure *(b)* the local change in capital stock devoted to IT in 1,000 EUR per employed persons between 2001 and 2015; Figure *(c)* the local change in capital stock related to CT in 1,000 EUR per employed persons between 2001 and 2015; and Figure *(d)* the local change in capital stock related to software and databases in 1,000 EUR per employed persons between 2001 and 2015. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. Own illustration.

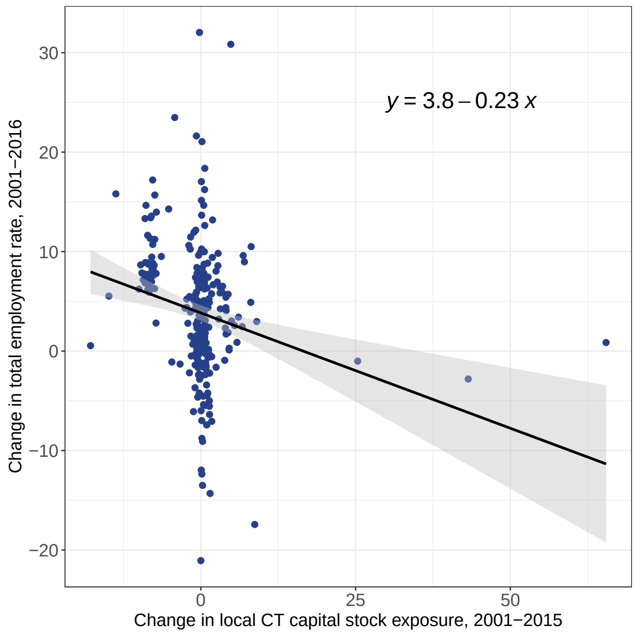
Figure B.3 **Local exposure to automation and change in total employment rate**



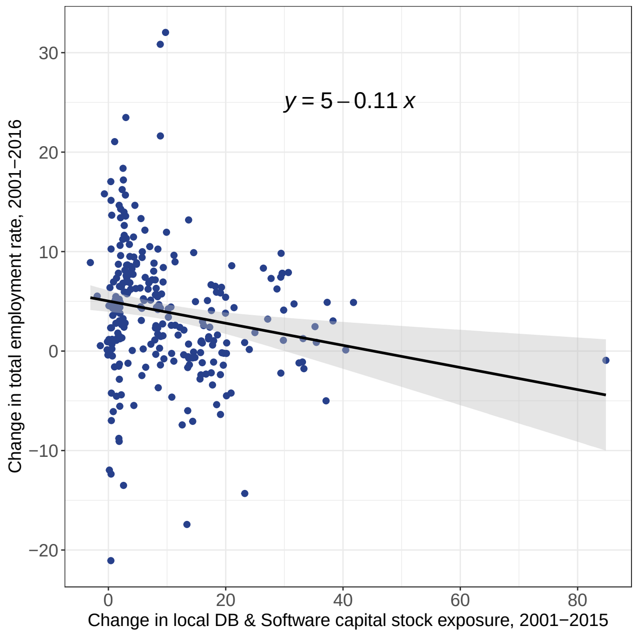
(a) **Change in local robot exposure**



(b) **Change in local IT exposure**



(c) **Change in local CT exposure**



(d) **Change in local database & software exposure**

Source: IFR, EU-KLEMS, SBS employment data, ARDECO.
Notes: The figures illustrate the unconditional correlation between the exposure to robots and ICT across EU regions (including UK regions) and the change in the local employment rate (employment relative to working age population 15-64). Figure *(a)* shows the correlation for the local change in robots per 1,000 employed persons between 2001 and 2016; Figure *(b)* for the local change in capital stock devoted to IT in 1,000 EUR per employed persons between 2001 and 2015; Figure *(c)* for the local change in capital stock related to CT in 1,000 EUR per employed persons between 2001 and 2015; and Figure *(d)* for the local change in capital stock related to software and databases in 1,000 EUR per employed persons between 2001 and 2015. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. Own illustration.

Table B.1 **Effects of automation on non-manufacturing employment in EU regions, 2001-2016**

Dependent variable:	*Employment growth, 2001-2016*				*Change in employment rate, 2001-2016*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Robots$	1.155**	-	1.173**	0.941**	0.335	-	0.386*	0.306*
	(0.513)	(-)	(0.540)	(0.416)	(0.215)	(-)	(0.220)	(0.179)
ΔIT	-	0.442	0.870	0.925*	-	-0.312	-0.171	-0.152
	(-)	(0.519)	(0.599)	(0.504)	(-)	(0.380)	(0.376)	(0.354)
ΔCT	-	-0.291	-0.288	-0.339	-	-0.148	-0.146	-0.164
	(-)	(0.343)	(0.291)	(0.288)	(-)	(0.241)	(0.197)	(0.205)
$\Delta Software\&Database$	-	0.108	0.0574	0.0233	-	-0.140**	-0.157**	-0.169**
	(-)	(0.109)	(0.132)	(0.130)	(-)	(0.0652)	(0.0789)	(0.0779)
Observations	270	270	270	270	270	270	270	270
Manufacturing share	Y	Y	Y	Y	Y	Y	Y	Y
Socio-demographic controls	Y	Y	Y	Y	Y	Y	Y	Y
$\Delta TradeChina$	N	N	N	Y	N	N	N	Y
Country-FE	Y	Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap Wald statistics	13.20	-	12.46	14.75	13.20	-	12.46	14.75

Notes: Standard errors in parentheses are clustered by 98 NUTS-1 regions. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on robot stocks from South Korea. ΔIT, ΔCT and $\Delta Software\&Database$ capture the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. * p<0.1, ** p<0.05, *** p<0.01.

Table B.2 **Effects of automation on employment growth in individual manufacturing industries in EU regions, 2001-2016**

Dependent variable:					*Employment growth, 2001-2016*				
Industry code:	*C10-C12*	*C13-C15*	*C16-C18*	*C19-C23*	*C24-C25*	*C26-C27*	*C28*	*C29-C30*	*C31-C33*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta Robots$	-0.762	-1.296	0.0380	-1.398*	-0.788	-4.785***	0.175	-6.036***	-0.0992
	(0.641)	(1.083)	(0.433)	(0.815)	(0.777)	(1.766)	(0.789)	(1.955)	(1.310)
ΔIT	1.825*	-0.888	2.117**	1.681	4.807**	0.726	2.407	-7.381***	-1.264
	(1.076)	(1.551)	(0.844)	(1.230)	(2.062)	(2.474)	(1.887)	(2.848)	(2.802)
ΔCT	-0.146	0.211	-0.0166	-0.435	0.247	-0.636	0.302	2.726	-3.644***
	(0.569)	(0.680)	(0.291)	(0.520)	(0.838)	(1.113)	(0.872)	(2.087)	(1.254)
$\Delta Software\&Database$	0.141	-1.140**	-0.836***	-0.615**	-0.859	-1.256***	-1.002*	0.196	1.187*
	(0.374)	(0.523)	(0.312)	(0.276)	(0.670)	(0.467)	(0.555)	(0.817)	(0.700)
Observations	270	270	270	270	270	270	270	270	270
Manufacturing share	Y	Y	Y	Y	Y	Y	Y	Y	Y
Socio-demographic controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
$\Delta TradeChina$	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap Wald statistics	14.21	14.21	14.21	14.21	14.21	14.21	14.21	14.21	14.21

Notes: Standard errors in parentheses are clustered by 98 NUTS-1 regions. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on the US robot stocks. ΔIT, ΔCT and $\Delta Software\&Database$ capture the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. * p<0.1, ** p<0.05, *** p<0.01. *Food, beverages and tobacco* (C10-C12); *textiles, apparel and leather* (C13-C15); *wood, paper and printing* (C16-C18); *petroleum, chemicals, pharmaceutical, plastic, and non-metallic mineral products* (C19-C23); *basic metals and fabricated metal products* (C24-C25); *computer, electronic products and electrical equipment* (C26-C27); *machinery* (C28); *motor vehicles and other transport* (C29-C30); and, *furniture and other manufacturing* (C31-C33). * p<0.1, ** p<0.05, *** p<0.01.

Table B.3 **Effects of automation on the change in employment rate in individual manufacturing industries in EU regions, 2001-2016**

Dependent variable:	*Change in employment rate, 2001-2016*								
Industry code:	*C10-C12*	*C13-C15*	*C16-C18*	*C19-C23*	*C24-C25*	*C26-C27*	*C28*	*C29-C30*	*C31-C33*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta Robots$	-0.0114	0.00877	-0.00563	-0.0195*	-0.0196*	-0.0527***	-0.00249	-0.0246	0.000220
	(0.0104)	(0.0159)	(0.00738)	(0.00997)	(0.0106)	(0.0173)	(0.00770)	(0.0295)	(0.0116)
ΔIT	-0.0153	-0.0242*	0.0107	0.0187	0.0521*	-0.0164	0.00900	-0.0477	0.0172
	(0.0169)	(0.0126)	(0.0105)	(0.0168)	(0.0305)	(0.0167)	(0.0115)	(0.0318)	(0.0179)
ΔCT	0.0151**	0.0126*	0.000246	0.00392	0.00873	0.0189*	0.0162**	0.0188	-0.0309***
	(0.00671)	(0.00738)	(0.00519)	(0.00977)	(0.0128)	(0.0102)	(0.00773)	(0.0128)	(0.0119)
$\Delta Software\&Database$	0.000517	0.00178	-0.00611**	-0.0111***	-0.00335	-0.0268***	-0.00424	0.000929	0.00785
	(0.00410)	(0.00502)	(0.00290)	(0.00381)	(0.00679)	(0.00528)	(0.00452)	(0.00644)	(0.00615)
Observations	270	270	270	270	270	270	270	270	270
Manufacturing share	Y	Y	Y	Y	Y	Y	Y	Y	Y
Socio-demographic controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
$\Delta TradeChina$	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap Wald statistics	14.21	14.21	14.21	14.21	14.21	14.21	14.21	14.21	14.21

Notes: Standard errors in parentheses are clustered by 98 NUTS-1 regions. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on the US robot stocks. ΔIT, ΔCT and $\Delta Software\&Database$ capture the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. * p<0.1, ** p<0.05, *** p<0.01. *Food, beverages and tobacco* (C10-C12); *textiles, apparel and leather* (C13-C15); *wood, paper and printing* (C16-C18); *petroleum, chemicals, pharmaceutical, plastic, and non-metallic mineral products* (C19-C23); *basic metals and fabricated metal products* (C24-C25); *computer, electronic products and electrical equipment* (C26-C27); *machinery* (C28); *motor vehicles and other transport* (C29-C30); and, *furniture and other manufacturing* (C31-C33). * p<0.1, ** p<0.05, *** p<0.01.

Table B.4 **Effects of automation on employment in selected service industries in EU regions, 2001-2016**

Dependent variable:	*Employment growth, 2001-2016*				*Change in employment rate, 2001-2016*			
Industry code:	*G-I*	*K-L*	*M-N*	*O-U*	*G-I*	*K-L*	*M-N*	*O-U*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Robots$	0.629**	0.304	1.101**	0.0189	0.102*	0.00974	0.103***	-0.00767
	(0.308)	(0.496)	(0.531)	(0.236)	(0.0526)	(0.0103)	(0.0394)	(0.0444)
ΔIT	0.786	2.189**	3.410***	-1.224***	0.0490	0.0494	-0.109	-0.338***
	(0.523)	(0.876)	(1.153)	(0.424)	(0.109)	(0.0317)	(0.124)	(0.0954)
ΔCT	-0.0498	-0.408	-0.289	0.178	-0.0147	-0.0132	-0.00374	0.0237
	(0.320)	(0.398)	(0.658)	(0.283)	(0.0540)	(0.0127)	(0.0577)	(0.0642)
$\Delta Software\&Database$	0.0843	-0.278	-0.639*	0.196	-0.0183	-0.0110**	-0.0682*	-0.0337
	(0.123)	(0.187)	(0.360)	(0.125)	(0.0211)	(0.00510)	(0.0380)	(0.0213)
	(0.123)	(0.360)	(0.125)	(0.0211)	(0.0380)	(0.0213)		
Observations	270	270	270	270	270	270	270	270
Manufacturing share	Y	Y	Y	Y	Y	Y	Y	Y
Socio-demographic controls	Y	Y	Y	Y	Y	Y	Y	Y
$\Delta TradeChina$	Y	Y	Y	Y	Y	Y	Y	Y
Country-FE	Y	Y	Y	Y	Y	Y	Y	Y
Kleibergen-Paap Wald statistics	14.21	14.21	14.21	14.21	14.21	14.21	14.21	14.21

Notes: Standard errors in parentheses are clustered by 98 NUTS-1 regions. All specifications are estimated including a constant, the regional employment share in manufacturing, and region-specific socio-demographic covariates such as the employment share of females, individuals older than 54 years, foreign-born, and medium- and high-skilled individuals. All covariates are added as initial values from 2001. In addition, country-fixed effects are included. $\Delta Robots$ denotes the change in the local robot exposure in 2001-2016 calculated according to Equation 1 (per 1,000 employed persons). $\Delta Robots$ is instrumented with the change in the robot exposure based on robot stocks from the United States. ΔIT, ΔCT and $\Delta Software\&Database$ captures the change in the local ICT exposure in 2001-2015 calculated according to Equation 2 (in 1,000 EUR per employed persons). $\Delta TradeChina$ refers to the change in the local exposure in 2001-2016 to net exposure with China. The sample excludes regions from Croatia, Cyprus, Malta, Luxembourg and Latvia. EU regions (including NUTS-2 regions of the UK) are defined in accordance with NUTS-2 codes of 2016. *Wholesale and retail, transportation and storage, and accommodation and food service activities* (G-I); *financial and insurance, and real estate activities* (K-L); *profession and scientific activities, administrative and support services* (M-N); and *public administration, education, arts, entertainment, other services* (O-U). * p<0.1, ** p<0.05, *** p<0.01.

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