Labor Market Impacts of Automation in Core and Peripheral Regions*

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Abstract

This paper examines labor market adjustments to robots, ICT, and software and database technologies across 187 NUTS-2 regions between 1995-2017. By clustering regions by their initial characteristics, we show that the impact of automation is mediated by regions' structural conditions. Robot adoption increase employment mainly in high-productivity core regions, while software and database technologies drive employment growth in lower-productivity regions. These results reveal a dual pattern of digital automation: physical automation benefits advanced industrial and service economies, whereas organizational automation supports catch-up in peripheral areas, highlighting how different technologies can either amplify or reduce regional inequalities in Europe.

Keywords: Automation technology, Labor market, Productivity, Sectoral composition.
JEL Codes: J21, O33, R23.

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1 Introduction

Empirical evidence on how digital and automation technologies affect regional labor markets in high-income countries remains mixed. For example, Acemoglu and Restrepo (2020) document that industrial robots have a net negative impact on U.S. employment. In Europe the evidence is more nuanced. While early studies confirmed negative employment effects (Chiacchio et al. 2018), subsequent research uncovered substantial sectoral and geographic variation. Specifically, Dauth et al. (2021) and Jestl (2024) demonstrate that job losses in manufacturing caused by robots are often offset by employment gains in services. Geographical heterogeneity remains an open debate: Reljic et al. (2023) find positive employment effects primarily in Europe's technologically advanced and high-productivity "core" regions, whereas Bachmann et al. (2024) show stronger positive effects in lower-cost, Eastern European regions. These contrasting findings underscore the importance of moving beyond national averages to understand how specific regional characteristics mediate the employment impacts of digital and automation technologies.

In this paper we focus on two key structural and path dependent regional features that may moderate the impact of digital and automation technologies on labor markets: productivity and industrial composition.[1] We investigate regional asymmetries in the labor market impacts of three different groups of digital and automation technologies: industrial robots (physical automation, mainly in industry), information and communication technology (ICT) (enabling digital infrastructures in both industry and services), and software & databases (SDB) (intangible technologies for cognitive and organizational automation and augmentation). Using data from 187 NUTS-2 regions across 14 European countries from 1995 to 2017, we examine how regional labor market responses vary according to initial structural and productivity characteristics. To achieve this, we first classify regions into four distinct clusters based on their initial industrial structure and productivity levels in 1995. We then analyze how these baseline differences shape regional labor-market adjustments to the adoption of digital and automation technologies.

Recent theoretical advances suggest that automation initiates a race between a labor-displacing substitution effect (Acemoglu and Restrepo 2020) and a labor-creating productivity effect (Bessen 2019). The substitution effect primarily targets routine tasks, which are abundant in manufacturing and administrative occupations (Autor et al. 2003; Goos et al. 2014; Michaels et al. 2014). In contrast, the productivity effect–which can lower prices,

[1]The literature has consistently shown that EU regions are characterized by a core-periphery structure, where productivity convergence is more an exception than a rule (Fagerberg et al., 1997; Verspagen, 2010; Wirkierman et al., 2018), and where policies supporting diversification towards related industries may instead further increase diversity among regions (Pinheiro et al., 2022; Rigby et al., 2022).

increase demand, and spur the emergence of new complementary tasks–is contingent upon a region's pre-existing capabilities, including its skill base and innovative potential (Boschma 2017; Balland and Boschma 2021; Caravella et al. 2023; Wirkierman et al. 2024). High-productivity "core" regions are typically better equipped to capitalize on this productivity effect by generating new high-skilled jobs complementary to the adopted technologies, both within and across industries. Conversely, lower-productivity "peripheral" regions risk falling behind and facing significant job displacement. This framework thus underscores the importance of regional heterogeneity when studying the impacts of automation.

Our empirical strategy proceeds in two steps. First, we classify regions into distinct clusters based on their 1995 sectoral composition and labor productivity using a K-means clustering algorithm. Sectoral composition captures variation in regional exposure to job automation risk, which differs substantially across agriculture, industry, and services. Labor productivity reflects differences in regional technological capabilities and indicates how effectively the local labor force can complement new technologies, leverage productivity gains, or facilitate the creation of new occupations.

Second, we estimate how three distinct digital and automation technologies—robots, ICT, and SDB—affect regional labor-market outcomes, specifically the employment-to-population ratio and average wages. To identify the causal impacts at the regional level, we employ a shift-share instrumental variable strategy. Specifically, we measure regional technology exposure based on initial employment shares by industry, instrumented by technology adoption rates within the same industries in the U.S. context. By interacting these adoption measures with the previously defined regional clusters, we are able to assess how initial regional characteristics moderate the labor-market impacts of digital and automation technologies.

Our analysis yields three main findings. First, the labor-market impacts of digital and automation technologies are highly path-dependent and vary significantly by technology type. Aggregating across regions conceals critical differences: at the aggregate level, the effects of robots and ICT on employment and wages become statistically insignificant once endogeneity is addressed. However, disaggregating by initial sectoral structure and productivity levels reveals pronounced regional differences, underscoring that the relevance of initial conditions varies across technologies.

Second, we document substantial variation in the employment effects of robots, driven primarily by regional productivity and initial industrial specialization. Physical automation (Robots) significantly boost employment, but exclusively in high- and medium-productivity regions capable of generating complementary service-sector jobs in regions initially specialized both in manufacturing and services. Conversely, robot adoption shows no significant impact in low-productivity, agriculture-intensive peripheral regions. This divergence implies that productivity-enhancing gains from robots do not materialize uniformly, and are instead realized primarily through the growth of service occupations in manufacturing-intensive core regions.

Third, the impact of organizational automation technologies (SDB) is markedly different. These intangible digital tools—such as enterprise resource planning (ERP) systems, supply chain management software, data analytics, and production control systems—positively affect employment only in low-productivity agricultural regions. This suggests that, in lagging regions, the productivity-enhancing effects of these technologies outweigh their substitution effects, likely due to higher returns from technological investments where initial productivity was lower. Nevertheless, SDB adoption is associated with higher average wages, specifically in high-productivity, service-oriented regions, indicating a skill-biased technological effect.

Our work relates to several strands of literature. First, it relates to the extensive literature examining how digital automation technologies affect labor markets (Bessen 2019, Acemoglu and Restrepo 2020, Aghion et al. 2020, Vries et al. 2020, Webb 2019, Gregory et al. 2022). The emerging literature on regional impacts of robot adoption within Europe presents mixed results: some studies identify negative effects on regional employment (Chiacchio et al. 2018; Aghion et al. 2019), while others document positive effects or find no significant impacts (Dauth et al. 2021; Reljic et al. 2023; Jestl 2024). Most existing studies analyze aggregate technology effects without fully accounting for structural heterogeneity across regions. Our contribution extends this literature by explicitly examining how the initial sectoral composition and productivity levels of regions shape their differential responses to distinct digital and automation technologies. Our findings complement those of Reljic et al. (2023), who identify positive employment impacts of robots primarily in core industrialized regions, a result consistent with our findings for high-productivity clusters.

Second, our work intersects with research on regional economic disparities and their determinants (Charlot et al. 2015; Fontagné and Santoni 2018; Xiao et al. 2018; Marchand et al. 2020; Aloi et al. 2021; Evenhuis et al. 2021). Recent studies attribute growing regional inequalities to varying capacities for innovation and skilled-labor attraction (Akçomak and ter Weel 2009; Lee and Rodriguez-Pose 2012; Iammarino et al. 2019; Boschma 2022). Our analysis contributes to this debate by demonstrating that differential regional impacts from digital and automation technologies arise from distinct regional specializations (agriculture-, industry-, or service-intensive), differing technological capabilities (high vs. low productivity), or the interplay between these factors.

The rest of the paper is organized as follows. Section 2 presents the data. Section 3 outlines the empirical approach, which relies on identifying clusters of regions and then on an IV shift-share approach to assess the labor market impact of technology penetration. Section

4 estimates the relation between labor market adjustments and technology penetration, emphasizing the heterogeneity in adjustments among clusters. Section 5 concludes.

2 Data

We combine several data sources to construct our dataset, which covers a sample of 187 NUTS-2 regions from 14 European countries over the period from 1995 to 2017.[2]

2.1 Labor Market Outcomes

We consider two key labor market outcomes: the employment-to-population ratio and the average wage. Both variables are derived from the Annual Regional Database of the European Commission (ARDECO) data and are available at the NUTS-2 level.[3] The employment-to-population ratio is calculated as the total number of employed persons aged 15–64 divided by the total population in the region.[4] The average wage refers to the average yearly wage per worker (expressed in thousands of €2015) and is determined by dividing the total compensation by the level of employment.

Given that ARDECO has a rather aggregated sectoral classification, we rely on this and define sectors (of economic activity) based on the NACE Rev.2 classification sectors.[5]

2.2 Digital Automation Technologies

We consider three distinct yet related digital and automation technologies: Robots (ROB),[6] Information and Communication Technology (ICT),[7] and Software and Databases (SDB).[8]

[2]The set of countries includes: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Spain, and Sweden. This sample covers a diverse set of EU economies, including high and low productivity, with diverse sectoral composition.

[3]ARDECO is developed and maintained by the Directorate-General for Regional and Urban Policy in collaboration with the Joint Research Center. It provides data from 1980 onwards on population, employment (both in terms of persons and hours worked), wages, labor costs, gross domestic product, and capital formation. This information is available at various territorial levels, including NUTS-3, NUTS-2, NUTS-1, and national. Employment figures are broken down by broad industry sectors.

[4]Yet, ARDECO data do not provide any information on labor market outcomes for different age groups.

[5]See appendix Table A.1 for the sectoral details.

[6]Robots are defined as 'programmed actuated mechanisms with a degree of autonomy to perform locomotion, manipulation, or positioning' (ISO 8373:2021).

[7]ICT encompasses communication technologies, which are described as 'specific tools, systems, computer programs, etc., used to transfer information among project stakeholders' (ISO 24765:2017), as well as information technologies, defined as 'resources required to acquire, process, store, and disseminate information' (ISO 24765:2017).

[8]SDB includes Computer Software, defined as 'computer programs, procedures, and possibly associated documentation and data pertaining to the operation of a computer system' (ISO 24765:2017), and Databases, which are 'collections of interrelated data stored together in one or more computerized files' (ISO 24765:2017).

Distinguishing between these technologies is central to our analysis, as they differ in their application and potential to substitute or complement labor. Robots represent a tangible form of mainly physical automation technology, embodying a new generation of machinery to perform manual tasks. Their primary use is in industries (e.g., automotive) agriculture, and to a smaller extend in services. ICT refers to the tangible hardware and network infrastructure essential for digital automation. In contrast, Software and Databases, when considered together, represent the intangible components of digital technologies, which can also be used for automating and/or augmenting cognitive and organizational processes, such as Enterprise Resource Planning (ERP) systems, Customer Relationship Management (CRM) software, and data analytics tools that reorganize workflows and manage information.

Robots. We measure the stock of robots in operation in each sector at the country level using data from the International Federation of Robotics (IFR); see Jurkat et al. (2022) for a comprehensive review of the data.

The IFR data report non-zero robot stocks for only three of our six aggregated sectors: Industry (B-E), Construction (F), and Non-Market Services (O-U). A significant share of robots in the IFR data (30%) are not allocated to a specific sector. Following Acemoglu and Restrepo 2020, we allocate these unspecified robots proportionally across the three sectors based on their share of the total number of robots in the country. We adopt this approach, in contrast to studies that discard unclassified robots (e.g. Graetz and Michaels 2018, Dauth et al. 2021), to construct a more comprehensive measure of robots' exposure across sectors.[9] For countries where sectoral data become available later, we impute historical robot stocks backwards by applying the average sectoral shares observed in the earliest available years, following the approach of Graetz and Michaels 2018. Our results are robust to alternative imputation methods, such as imputing based on the relative trend in robot stocks in each sector.

ICT and SDB. We measure the stock of ICT and SDB using the EU-KLEMS database (Release 2021). This database provides information on ICT and SDB net capital stock for each sector at the country level since 1995[10]. Our measures are based on the net capital stock (in chained linked volumes of 2015), derived from national accounts. As the EU-KLEMS data are reported in national currencies, we convert the amounts for non-euro countries into euros using the nominal exchange rate from EUROSTAT.

[9] According to Jurkat et al. (2022), the share of unclassified robots has decreased sharply over time.

[10] See Bontadini et al. (2021) for a comprehensive review

2.3 Confounding Factors

To isolate the effect of digital and automation technologies from other major changes affecting regional labor markets during this period, we include two key control variables. First, we control for changes in domestic demand using data on the real consumption index provided by the Inter-Country Input-Output database.[11] This accounts for the possibility that technology-induced productivity gains stimulate labor demand via increased product demand (Bessen 2019).

Second, we account for the rise in import competition from China using data from the OECD Trade in Value Added database.[12] Increased trade penetration, particularly in manufacturing, is a well-documented source of adverse labor market effects in high-income countries (Autor et al. 2013, Autor et al. 2015). Both of these control variables are calculated at the regional level (i.e., in shift shares) in thousands €2015 per worker in 1995.

3 Methodology

In this section, we present our methodology to estimate the impact of digital automation technologies on labor markets while accounting for heterogeneous impacts across European regions. We proceed in two steps. We first develop a regional typology by clustering regions into groups based on their initial (1995) sectoral specialization and labor productivity. We then present our empirical specification, which relies on a shift-share approach and instrumental variable (IV) strategy to account for endogeneity.

3.1 Clusters of European Regions

We cluster the 187 regions based on their economic specialization and labor productivity in 1995. We measure specialization using the share of employment in Agriculture (A), Industry (B-E + F), and Services (K-N + G-J + O-U) as three distinct variables. We measure the region's productivity using the gross value added per worker.

These two dimensions—sectoral structure and productivity—capture key initial conditions that may mediate the impact of digital and automation technology adoption on labor markets. The sectoral structure distinguishes between regions that are likely to adopt different digital automation technologies, which are integrated differently in the production process in different sectors (Pavitt 1984, Evangelista and Savona 2003, Dosi et al. 2021).

[11] OECD (2021), OECD Inter-Country Input-Output Database, http://oe.cd/icio. Release: November 2019.

[12] OECD (2021), OECD Trade in Value Added Database, http://oe.cd/tiva. Release: November 2021.

Sector specialization also shapes differences in the reallocation of labor across sectors following technology adoption (Autor and Salomons 2018). The initial productivity level captures, on the one hand, adoption differentials between high and low productive firms, clustered in different regions (Autor et al. 2020), and, on the other hand, heterogeneous impacts arising from differences in the initial endowments of skills and technologies.

We standardize the clustering variables using two distinct approaches to account for different sources of heterogeneity. First, to control for country-specific sectoral structures, we standardize the sectoral employment shares at the country level. This ensures that the clustering reflects meaningful variation within countries, rather than being driven by cross-country differences in economic specialization.[13] Instead, to account for differences in productivity between core and peripheral regions across the full European sample, we standardize the labor productivity measure across the entire sample.

We use a Principal Component Analysis (PCA) to identify the dimensions along which regions differ the most. Table 1 presents the PCA eigenvectors.

Table 1: Principal Component

	Principal Component (PC)			
	PC1	PC2	PC3	PC4
Productivity	0.26	0.78	0.57	0.00
Share of Agriculture in Emp.	-0.44	-0.39	0.72	0.36
Share of Industry in Emp.	-0.55	0.46	-0.38	0.59
Share of Service in Emp.	0.66	-0.18	-0.05	0.72
Standard Deviation	1.41	1.02	0.85	0.21
Proportion of Variance	0.52	0.28	0.19	0.01
Cumulative Proportion	0.52	0.80	0.99	1.00

Notes: This table presents eigenvectors of the principal components analysis. The eigenvectors refer to columns PC1 to PC4. Cluster variables include productivity and employment shares in agriculture (A), industry (B-E and F), and services (K-N, G-J, and O-U).

The first component (PC1) primarily reflects differences between service-intensive (positive) with respect to industry- and agriculture-intensive (negative). The second (PC2) and third components (PC3) distinguish industry-intensive and agriculture-intensive regions, respectively. The highest positive sign on the productivity component indicates that industry-intensive regions tend to be the most productive. These three principal components explain 99% of the variance. Principal Component 4 (PC4) serves as a residual.

[13] If we were to standardize at the European level, the resulting clusters would primarily reflect country-level differences, thus grouping observations by country.

We classify regions into four clusters using a k-means clustering algorithm.[14] Table 2 describes the clusters and their centers, that is, the within-cluster averages.

Table 2: Clusters and K-means

	Cluster	N	K-means			
			Agriculture	Industry	Service	Productivity
1	Service intensive (High)	43	-0.98	-1.15	1.44	0.55
2	Industry intensive (High)	69	-0.23	0.85	-0.61	0.37
3	Agriculture Intensive (Medium)	49	1.08	-0.17	-0.30	-0.04
4	Agriculture Intensive (Low)	26	0.21	-0.02	-0.19	-1.80

Notes: This table presents the clusters, the number of regions within them (N), and their within-cluster average in clustering variables. Clustering variables are expressed in standard deviation. Agriculture, Industry, and Service refer to the share of regional employment in these sectors, standardized at the country level, while productivity refers to the gross value added per worker, standardized over the entire sample.

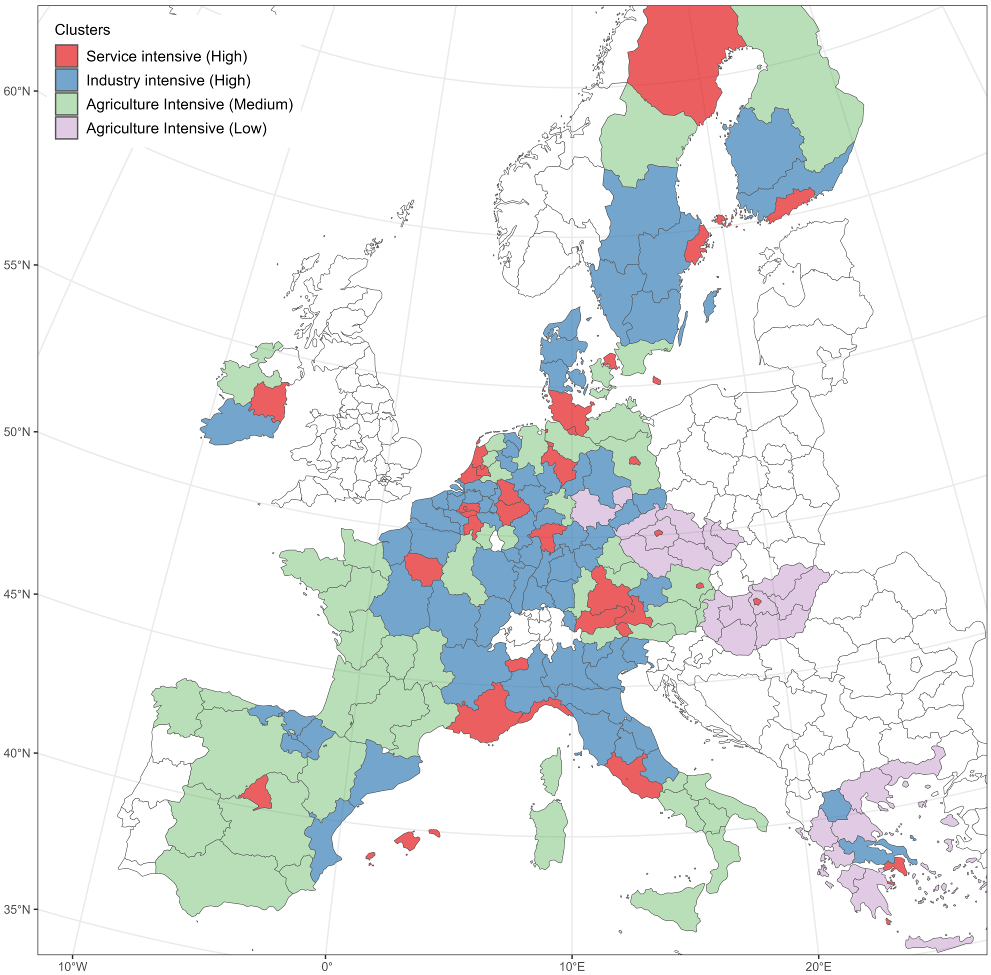
These four clusters of regions reflect differences in regional economic structure and performance. The first two clusters—service-intensive and industry-intensive—are high-productivity regions, comprising 43 and 69 regions, respectively. The remaining two clusters are agriculture-intensive regions, which differ in their productivity levels. One group, consisting of 49 regions, shows average productivity, with cluster centers close to zero. The other group includes 26 regions and is characterized by low productivity, as indicated by the negative cluster average.

Figure 1 maps the geographical distribution of the clusters. Regions in red correspond to the service-intensive cluster, blue represents the industry-intensive cluster, and green indicates the agriculture-intensive clusters with medium productivity, and purple indicates low productivity.

We make three observations. First, a clear divergence in regional productive structures across Europe emerges. Service-intensive regions are heavily concentrated in parts of Northern and Western Europe, including several regions in France, Italy, and the Nordic countries. These 43 regions represent urban knowledge-based economic cores characterized by high productivity knowledge intensive service sector in 1995. They are endowed with high human capital and innovation capacity, and are well-positioned to create new, high-skilled

[14] Our preferred classification is based on three metrics: Within-cluster Sum of Squares (WSS), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Figure B.1 in the Appendix presents the goodness-of-fit based on these metrics, for sets ranging in size from 1 to 15. Both the WSS and AIC curves begin to level off around four clusters, as indicated by the diminishing slope, while the BIC curve also flattens at this point. This suggests that adding more clusters offers only marginal improvements in within-cluster variance. Thus, four clusters balance explanatory power and model simplicity, facilitating interpretation of results.

Figure 1: Geographic Distribution of Regional Clusters



Notes: This figure presents the geographical distribution of the clusters. Clusters are obtained using the K-means algorithm. The set of clustering variables includes the shares of employment in agriculture, industry, and services, standardized at the country level, and regional productivity, expressed as gross value added per worker, standardized over the entire sample.

tasks complementary to automation. Highly productive industry-intensive regions are more prevalent in Central Europe, particularly in Germany, Czechia, Austria, and Northern Italy, reflecting the strong manufacturing knowledge intensive base of these regions. These regions are most likely to adopt robots and benefit from a productivity boost from the adoption. Agriculture-intensive regions with average productivity are widely distributed, especially across France, Spain, and parts of Eastern Europe. These are regions that are peripheral to the above two groups of core highly productive regions, but also well connected to them (Wirkierman et al., 2024). In contrast, low-productivity agriculture-intensive regions are primarily located in Southern and Eastern Europe. These 26 regions represent the periphery in 1995, with the largest potential for productivity gains through the adoption of established, general-purpose technologies. This spatial distribution highlights the diversity of regional economic structures and confirms the divide in both sectoral specialization and productivity performance across European regions discussed in the literature on EU regional disparities.

Second, all capital cities are service-intensive regions.

Third, regions within countries tend to be similar to their neighbors, that is, they show spatial coherence, which is demonstrated by their geographical clustering. For instance, regions in Northern Italy tend to be industry-intensive, whereas those in the South are concentrated mostly on agriculture. Also, Western regions of France are agriculture-intensive, whereas those in the North and East of France tend to be industry-intensive.

3.2 Empirical Specification

Our empirical strategy aims to estimate the causal impact of technology adoption on regional labor market outcomes. Since the adoption of digital and automation is only observed at the country-industry level in our data, we construct a regional exposure measure using a shift-share design. To address the potential endogeneity of technology adoption, we instrument this measure with digital and automation technology adoption in the US, which captures global demand for digital and automation technologies, which is plausibly exogenous to economic shocks within any single European region.

We define our regional exposure to technology k as a shift-share variable, computed as:

$$x_r^k = \sum_i l_{ri} \Delta k_{ci}, \tag{1}$$

where l_{ri} is the share of employment in sector i within region r in 1995, and Δk_{ci} is the change in technology stock (per thousand workers) in sector i within country c between 1995 and 2017.

We instrument the sectoral change in technology stock in European regions with the sectoral change in technology stock in the US. Formally, our IV shift-share instrument is:

$$z_r^k = \sum_i l_{ri} \Delta k_{US,i}, \tag{2}$$

where $\Delta k_{US,i}$ is the change in technology stock (per thousand workers) in the US sector i between 1995 and 2017.

In our first stage regression, we regress the regional exposure on the IV shift-share regional exposure for each technology separately, such that:

$$x_r^k = \alpha + \beta z_r^k + u_r, \tag{3}$$

where x_r^k is given by Equation (1), z_r^k by Equation (2), and u_r is the error term. Table C.1, in the appendix, reports the first-stage estimates.[15] We obtain the predicted $\hat{x}_r^k$ to estimate our second-stage regression.

In our second stage regression, we estimate the regional labor market adjustments to digital automation technologies:

$$\Delta y_r = \alpha + \sum_k \beta_k \hat{x}_r^k + \gamma X' + \delta + u_r, \tag{4}$$

where Δy_r is the change in the outcome variable (employment-to-population ratio and average wage) in region r between 1995 and 2017, $\hat{x}_r^k$ is the instrumented regional exposure to each technology k in that region, and X is a vector of control variables, including the change in final domestic demand and the change in exposure to Chinese imports and the logarithm of the population in 1995. δ represents country-fixed effects and u is the error term.

We use the employment-to-population ratio instead of employment to account for changes in regional population, for instance due to migration or long term demographic changes. While the employment-to-population ratio mitigates the concern on the role of migration between regions, it remains an important unobserved channel that we cannot directly observe. Our results are thus the net effect on the regional labor market, which includes any induced migration flows. The change in average wage is calculated in log changes, whereas the change in the employment-to-population ratio is computed directly. Therefore, the coefficients on the wage regression can be interpreted as percentage changes, whereas for the employment regression, the coefficients represent the percentage point (pp.) change for a

[15] It is possible to infer from Table C.1 that there is a positive and strong correlation between the instrumented variable and the instruments. Therefore, we can be confident in the validity of our IV approach.

one-unit change in technology exposure at the regional level.

To test for heterogeneous effects in the impact of technologies on regions based on their characteristics, we estimate the same specification interacted with dummy variables for each of our four regional clusters.

4 Labor Market Adjustments and Heterogeneity Across European Regions

In this section, we present the estimates of the impact of digital automation technologies on employment and wages. We first present the average effects across all regions, and then turn to our main analysis of heterogeneity across regional clusters. We conclude the section by providing a series of validity checks for our instrumental variable strategy.

4.1 Overall Labor Market Adjustments

Table 3 presents the estimated coefficients for the OLS (Panel A) and the second-stage IV (Panel B) regressions.

Looking first at the employment-to-population ratio (Columns (1)-(3)), a comparison between OLS and IV results is suggestive of endogeneity. The significant positive OLS coefficient for robots, indicating higher employment in most exposed regions, becomes statistically insignificant in the IV specification. This suggests the OLS correlation is likely biased by other factors, such as infrastructure investments that boost both employment and robot adoption, or by reverse causality. For both robots and ICT, we find no significant effect on the employment rate over these 23 years when we account for endogeneity.

However, we find a positive and significant impact of software and databases. As shown in Column (3), the coefficient implies that a one-unit increase in software and databases exposure yields an average increase in regional employment-to-population ratio of 2.9 pp. between 1995–2017. This suggests that regions more exposed to intangible digital technologies over this period experienced an increase in employment. Given that the average change in software and database exposure during this time was 2.3, this corresponds to an estimated increase of 6.7 pp. in the employment-to-population ratio for the average region. Considering that the baseline average employment-to-population ratio in 1995 was 40%, this effect represents a substantial change—approximately 16% of the baseline level.

Turning to the average wage (Columns (4)-(6)), the significant OLS correlations also disappear when instrumenting technology exposure. Across all three technologies, we find no statistically significant average effect on regional wages (Panel B, Columns (4)-(6)).

The null average effects for robots and ICT over these 23 years could mask significant underlying dynamics. First, over such a long period, employment substitution effects may be compensated by, for instance, productivity gains (Aghion et al. 2022), demand growth (Vivarelli 1995), and the emergence of new tasks and occupations (Autor et al. 2024). The literature suggests that the effect can vary based on the time horizon or the specific sector of adoption. For example, Reljic et al. (2023) find a positive impact of robots stock on employment for the period 2011–2018 for a smaller sample of countries, while Jestl (2024) also finds no impact of robots on the employment rate for a similar number of countries included in our sample between 2001 and 2016, but finds a negative impact in manufacturing. Jaccoud et al. (2025) explicitly investigates digital and automation technologies impacts over their technologies' life cycles, and also find large positive impacts of robots on the employment rate during each cycle.

Crucially, these null average effects may conceal significant heterogeneity over the sectoral and technological characteristics of the regions adopting these digital and automation technologies. This is what we investigate in the next section.

4.2 Heterogeneity in Regional Labor Markets Adjustments

We now explore how the impacts of digital and automation technologies vary across our four regional clusters. Table 4 presents the results from the IV regressions where each technology exposure variable is interacted with region clusters.

Table 3: Labor Market Adjustments to Automation Technologies

	Regression - Change in outcome variable (1995-2017)					
	Δ Emp-to-pop. ratio $\times$ 100			Δ Average wage (in log) $\times$ 100		
	(1)	(2)	(3)	(4)	(5)	(6)
[A] *OLS*						
ROB	0.30	0.30	1.57^{**}	-1.07	-1.12	2.15
	(0.31)	(0.31)	(0.66)	(0.94)	(0.94)	(2.01)
ICT	3.11^{**}	3.13^{**}	2.72	-10.08^{**}	-11.43^{**}	-8.24
	(1.53)	(1.58)	(1.84)	(4.70)	(4.82)	(5.63)
SDB	0.25	0.27	-0.24	5.17^{**}	4.31^{**}	5.06^{*}
	(0.66)	(0.70)	(0.84)	(2.01)	(2.12)	(2.57)
Country FE	✓	✓	✓	✓	✓	✓
Demographics		✓	✓		✓	✓
Covariates			✓			✓
R^2	0.47	0.47	0.49	0.70	0.71	0.71
Adj. R^2	0.42	0.42	0.43	0.67	0.68	0.68
Num. obs.	187	187	187	187	187	187
[B] *IV*						
ROB	0.33	0.40	1.28	-1.14	-1.29	0.85
	(0.24)	(0.25)	(0.78)	(0.80)	(0.81)	(2.56)
ICT	0.56	0.53	-0.84	-6.02	-5.96	-9.70
	(3.01)	(2.99)	(3.09)	(9.80)	(9.79)	(10.15)
SDB	1.55	1.93^{*}	2.93^{**}	2.76	1.89	4.62
	(0.99)	(1.01)	(1.19)	(3.23)	(3.31)	(3.91)
Country FE	✓	✓	✓	✓	✓	✓
Demographics		✓	✓		✓	✓
Covariates			✓			✓
R^2	0.52	0.53	0.54	0.69	0.70	0.70
Adj. R^2	0.47	0.48	0.49	0.67	0.67	0.67
Num. obs.	187	187	187	187	187	187
F statistic	11.41	11.03	10.26	24.12	22.84	20.71

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the OLS (Panel A) and IV (Panel B) regressions of adjustments of the regional employment-to-population ratio, in Columns (1) to (3), and regional average wage per worker, in Columns (4) to (6), to a change in the regional penetration of robots, information and communication technology, and software and database. Regional exposure is constructed as a shift—share variable using the sectoral structure of employment in the region in 1995 and the change in the technology stock per thousand workers in the sector within the country. The change is instrumented with the change in the US in the corresponding sector. Regions are weighted by their population in 1995. Demographics control includes the population in 1995 in logarithms. Covariates include the change in imports from China (in shift-share) and the change in the real consumption index (in shift–share), both over the same period. Controls include country-fixed effects.

Table 4: Labor Market Adjustments to Technology Penetration at the Cluster Level (IV)

	IV Regression - Change in outcome variable (1995-2017)					
	Δ Emp-to-pop. ratio × 100			Δ Average wage (in log) × 100		
	(1)	(2)	(3)	(4)	(5)	(6)
Robot						
ROB × Service intensive (High)	1.06*	1.16*	4.82***	−2.18	−2.46	2.20
	(0.60)	(0.62)	(1.26)	(2.16)	(2.22)	(4.63)
ROB × Industry intensive (High)	1.74***	1.77***	4.17***	−1.50	−1.60	1.37
	(0.54)	(0.55)	(0.90)	(1.94)	(1.95)	(3.31)
ROB × Agriculture intensive (Medium)	0.76	0.74	3.64***	0.15	0.20	4.62
	(0.58)	(0.58)	(1.04)	(2.08)	(2.08)	(3.80)
ROB × Agriculture intensive (Low)	−2.21***	−2.14***	−0.19	−5.88**	−6.08**	−3.21
	(0.78)	(0.79)	(0.97)	(2.80)	(2.83)	(3.54)
Information and Communication Technology						
ICT × Service intensive (High)	−4.45	−4.59	−2.86	−3.48	−3.08	−2.77
	(3.45)	(3.46)	(3.45)	(12.32)	(12.36)	(12.65)
ICT × Industry intensive (High)	−4.97	−4.66	−5.00	20.21	19.30	15.37
	(4.55)	(4.58)	(4.55)	(16.27)	(16.38)	(16.67)
ICT × Agriculture intensive (Medium)	−1.64	−0.96	0.65	7.17	5.18	0.97
	(4.34)	(4.46)	(4.69)	(15.51)	(15.93)	(17.19)
ICT × Agriculture intensive (Low)	−2.37	−2.94	−2.55	−38.13	−36.47	−35.96
	(6.48)	(6.54)	(6.36)	(23.14)	(23.37)	(23.31)
Software and Database						
SDB × Service intensive (High)	0.52	0.75	0.00	8.74**	8.05**	8.79*
	(1.08)	(1.13)	(1.22)	(3.84)	(4.04)	(4.47)
SDB × Industry intensive (High)	1.02	1.11	1.30	−0.58	−0.87	2.28
	(1.36)	(1.37)	(1.53)	(4.86)	(4.90)	(5.61)
SDB × Agriculture intensive (Medium)	0.90	0.87	−0.51	−2.46	−2.37	0.24
	(1.55)	(1.55)	(1.98)	(5.53)	(5.54)	(7.27)
SDB × Agriculture intensive (Low)	9.54***	9.75***	9.55***	13.10	12.49	12.47
	(2.47)	(2.49)	(2.42)	(8.82)	(8.90)	(8.89)
Country FE	✓	✓	✓	✓	✓	✓
Demographics		✓	✓		✓	✓
Covariates			✓			✓
R^2	0.66	0.66	0.68	0.74	0.74	0.74
Adj. R^2	0.60	0.59	0.62	0.69	0.69	0.69
Num. obs.	187	187	187	187	187	187

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the IV regressions of adjustments of the regional employment-to-population ratio, in Columns (1) to (3), and regional average wage per worker, in Columns (4) to (6), to a change in the regional penetration of robots, information and communication technology, and software and database by cluster. Regional exposure is constructed as a shift–share variable using the sectoral structure of employment in the region in 1995 and the change in the technology stock per thousand workers in the sector within the country. The change is instrumented with the change in the US in the corresponding sector. Clusters are obtained using the K-means algorithm. Clustering variables refer to employment shares in agriculture, industry, and services, standardized at the country level, and productivity, expressed as gross value added per worker, standardized over the entire sample. Regions are weighted by their population in 1995. Demographic control includes the population in 1995 in log. Covariates include the change in imports from China (in shift–share) and the change in the real consumption index (in shift–share), both over the same period. Controls include country-fixed effects.

Columns (1) to (3) highlight significant heterogeneity across regions in the effects on the employment-to-population ratio, particularly regarding robot exposure. Column (3), which includes all covariates, indicates that a one-unit increase in robot exposure raises the employment-to-population ratio by 4.17 pp. in high-productivity industrial regions and by 4.82 pp. in high-productivity service regions. Given the average increase in robot exposure between 1995 and 2017 was 2.7 units in industry-intensive regions and 1.31 units in service-intensive regions, these estimates correspond to substantial increases of approximately 11 pp. and 6.3 pp., respectively. While agricultural regions exhibit a significant positive effect, this effect becomes insignificant for regions specialized in agruculture with low productivity.[16] These findings align with Reljic et al. (2023), who report positive employment effects of robot adoption predominantly in 'core' manufacturing and service-oriented countries.

Building on both theoretical and empirical literature, we propose two explanations for this regional difference. The first explanation relates to productivity gains within industries adopting robots. In these industries, robot adoption increases productivity, leading to expanded output and sales, which in turn offset initial worker displacement (Aghion et al. 2022). However, this productivity-driven employment boost occurs predominantly in regions that were technologically advanced before robot adoption, possibly because they were already using earlier generations of robots (Wirkierman et al. 2024).

The second explanation emphasizes cross-sectoral spillovers. Specifically, investments in robots stimulate demand for new tasks and jobs in other sectors within the same region (Autor and Salomons 2018; Autor et al. 2024). This explanation aligns closely with emerging evidence suggesting robots negatively affect regional manufacturing employment (Jestl 2024), but positively affect employment in regional service sectors (Jaccoud et al. 2025). Hence, in manufacturing-intensive regions, robot adoption likely fosters growth in services due to increased manufacturing productivity. This spillover effect is smaller in regions already specialized in services, due to their limited manufacturing base. Finally, in low-productivity, agriculture-intensive regions within our European sample, these new services do not emerge at all.

While ICT exposure does not produce statistically significant employment effects in any of the four regional clusters, the impact of SDB exposure is notably different. Specifically, the positive average effect of SDB on employment rates reported in Table 3 is primarily driven by low-productivity agricultural regions. In these regions, a one-unit increase in SDB exposure corresponds to a 9.55 pp. rise in the employment-to-population ratio. Given that the average change in SDB exposure in these regions is 0.52, this translates into a substantial

[16]These regions show a negative effect, but it becomes insignificant after controlling for trade and business cycles in column (3).

employment ratio increase of approximately 4.97 pp.

Software and database technologies—such as enterprise resource planning (ERP) systems, supply chain management software, data analytics, and production control systems—primarily assist and augment industrial operations rather than fully automate them. These technologies typically manage information processing, coordination, and optimization, complementing the physical production tasks carried out by humans and machines. Because SDB technologies increase productivity without directly displacing jobs, their adoption positively influences regional employment. Interestingly, this positive effect occurs exclusively in regions that were initially lagging in productivity, highlighting the potential for these intangible technologies to generate new employment opportunities precisely where productivity gaps were largest. This finding supports a 'technological catch-up' process, where the adoption of foundational digital tools for management and organization may provide a productivity and employment boost in lagging regions.

Turning to wages, columns (4) to (6) reveal a modest wage premium from SDB in high-productivity service-intensive regions: a one-unit increase in exposure increases the average wage by roughly 8.8 percent. In technologically advanced, more productive, and service oriented regions, new software complements high-skilled workers, increasing their productivity and wages without creating a significant number of new jobs.

Overall, the evidence points to sharply divergent regional labor-market responses to digital and automation technologies. Robot adoption boosts employment only in Europe's high-productivity "core" areas, whereas intangible digital tools such as SDB generate employment gains mainly in low-productivity "lagging" areas. ICT capital, by contrast, shows no discernible employment effect in any cluster. These patterns imply an uneven distribution of digital gains: core regions harvest substantial productivity pay-offs from robots, while many Southern and Eastern regions are still absorbing the benefits of intangible technologies.

4.3 Validity Checks

To assess the robustness of our IV estimates, we follow the methodology proposed by Goldsmith-Pinkham et al. (2020) to decompose the overall IV effect. We interpret the 2SLS coefficient as a weighted average of instrument-specific treatment effects derived from each individual country-industry instrument.In particular, we decompose the IV estimator into the Rotemberg weights (α_k) and the just-identified estimators (β_k). This approach evaluates the extent to which the overall estimates are driven by a subset of instruments, i.e., how much each instrument contributes to the overall IV estimate, and therefore also indicate the potential influence of any misspecification. If an individual instrument is misspecified, its influence on the aggregate estimate is rather limited when its corresponding weight, α_k, is small (Goldsmith-Pinkham et al., 2020). This diagnostic is relevant because if the overall estimate is driven by a few high-share instruments, it may not be robust. We implement this approach for each of the technologies analyzed.

Robots. Concerning robots, Table D.1 provides a summary of the five most influential instruments. The top three instruments—`DE_B-E`, `ES_B-E`, and `FR_B-E`—account for over 75% of the total Rotemberg weight and yield similar local IV estimates (ranging from 0.019 to 0.032). This reflects the fact that these large European economies are central to European manufacturing and that robots are mainly adopted in the manufacturing sector.

Figure D.1 plots the instrument-specific estimates of β_k against their corresponding Rotemberg weights α_k. Each point represents a country-industry instrument, where the size of the dot represents the Rotemberg weights. All the instruments displayed have positive weights, and most estimates are centered around the overall IV estimate in Table 3, indicated by the horizontal dashed line. In line with what is observed in Table D.1, the graph shows that the German manufacturing sector has the largest Rotemberg weights.

To assess whether the largest instrument influences the overall IV estimation, we re-estimated Columns (3) and (6) of Panel B in Table 3, this time excluding German regions. The results, presented in Table D.2, remain largely consistent with those reported in the original IV regression in Table 3.

Information and Communication Technology (ICT). Turning to ICT, Table D.3 summarizes the top five contributing instruments. The most influential instrument is `SE_B-E`, with a weight of $\alpha_k = 0.510$, accounting for 11.9% of the absolute weight sum. Its local estimate, $\beta_k = 0.030$, is close to the overall average. The remaining key instruments tend to be in the service sector `K-N`, which is consistent with the fact that these technologies are adopted mainly in knowledge-intensive services.

Figure D.2 depicts some dispersion in both the weights and the estimated effects. Although some instruments (e.g., `DE_A`, `IE_O-U`) yield large β_k values, their weight is relatively small, so it does not pose a major concern to the overall IV estimate. Overall, this analysis suggests that the IV estimate for ICT is influenced by a more diverse and heterogeneous set of instruments than in the case of robots. As for robots, we have re-estimated the IV estimates of our outcome variables, excluding Swedish regions. Table D.3 reports the results, which are largely in line with what is observed in Columns (3) and (6) from Panel B in Table 4.

Software and Database (SDB). Table D.5 summarizes the top five contributing instruments for SDB. Notably, `FR_K-N` and `FR_G-J` are the two most influential, accounting for approximately 24% of the total weight. In this case, there is a clear predominance of the `G-J` sector, which includes information and communication technologies—a major producer and user of software.

Figure D.3 shows relatively little heterogeneity in both α_k and β_k. This limited dispersion suggests a relative homogeneity across instruments and increases confidence in the stability of the estimate. Further, Table D.6 reproduces the coefficients displayed in Panel B of Columns (3) and (6) from Table 4, showing that the results hold when excluding French regions.

5 Conclusion

This paper examines the labor market adjustments to digital automation technologies in 187 regions located across 14 European countries for 1995–2017. We use several sources of data to measure the penetration of robots, ICT, and software and database. By clustering regions based on their initial sectoral specialization and productivity, we find that labor market adjustments to different digital automation technologies depend on these path-dependent regional characteristics. Our findings underscore the importance of accounting for regional differences to assess the impact of automation technologies.

Our work delivers three key findings. First, the impact of digital and automation technologies on labor markets is both path-dependent and technology-specific. While no significant effects are observed at the aggregate regional level, important differences emerge across regions with varying initial sectoral structures and productivity levels. Second, robot adoption significantly increases employment in high- and medium-productivity regions, in both manufacturing and services, whereas it has no impact in lagging, low-productivity, agriculture-intensive regions. Third, the opposite pattern holds for software and databases: these intangible digital technologies increase employment mainly in low-productivity, agriculture-based regions, while in high-productivity, service-oriented regions, they are associated with higher average wages, indicating a skill-biased effect.

Incorporating a regional perspective is crucial for understanding Europe's responses to automation adoption, particularly given the well-documented core–periphery divide (Reljic et al. 2023). Our cluster analysis highlights a pronounced productivity gap between Western and Northern regions compared to Eastern and Southern ones. Although it is not a direct measure of capabilities—as these are difficult to measure (Boschma 2017)—we argue that it reflects the high degree of heterogeneity in knowledge-based activities, skills, and infrastructure, which influence technology diffusion (Ciarli et al. 2021) and the possibility of regions to benefit from automation. The literature on automation and labor markets identifies several counterbalancing effects, such as productivity gains and the creation of new tasks, that can mitigate potential negative employment impacts. However, for these effects to materialize, regions require complementary knowledge endowments that enable such mechanisms.

All in all, these results suggest that regional responses to technology adoption are influenced by their existing technological capabilities. Structural characteristics play a critical role in determining whether regions can reap the employment benefits of technology adoption. This dynamic may exacerbate the pre-existing core–periphery divide in Europe, emphasizing the need for tailored policies to address these disparities. Moreover, in light of recent advancements in artificial intelligence and its widespread potential, the complementarity between emerging technologies and skills and abilities to effectively use these technologies is key.

We argue that our work has important policy implications, in particular for EU cohesion. Local public policies aimed at the introduction of automation technologies to benefit all workers should consider labor market specificities such as regional workforce specialization and technology capabilities. Our results suggest a two-pronged approach for EU cohesion policy. For lagging regions, industrial policy should prioritize diffusion of and training for foundational digital tools like SDB to help close the productivity gap. For traditional industrial regions, policy could focus on skills upgrading and supporting the growth of the high-skilled business service sector to capitalize on spillovers from automation.

This work also opens avenues for future research. First, incorporating data on occupations and skills would enhance our understanding of employment adjustments. However, consistent data from the European Union Labor Force Survey (EU-LFS) are only available from 2011 onward, which would limit the analysis period. Second, while we account for migration indirectly through population changes by using the employment-to-population ratio, we do not explicitly examine worker reallocation between regions as a response to automation technologies. These questions require further exploration in future studies.

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Appendices

A Data

This appendix reports, in Table A.1, the aggregation of NACE sections used in the analysis.

Table A.1: Sectors of economic activities and NACE sections

	Sector	NACE Rev. 2	NACE Rev. 1.1
A	Agriculture	A	A, B
B-E	Industry	B, C, D, E	C, D, E
F	Construction	F	F
G-J	Market Services	G, I, H, J	G, H, I
K-N	Financial Business Services	K, L, M, N	J, K
O-U	Non-Market Services	O, P, Q, R, S, T, U	L, M, N, O, P, Q

Notes: This table presents the classification of sectors used in the analysis. This classification is derived from the NACE classifications such to be compatible across the two versions Rev. 1.1 and Rev. 2.

Table A.2: Descriptive Statistics

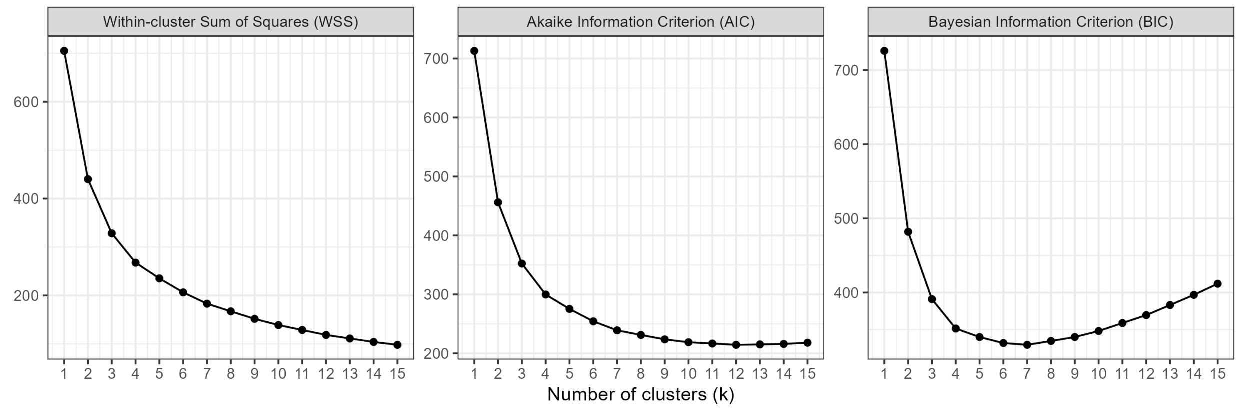
Variable	Mean	SD	Min	Q1	Q2	Q3	Max	N
Δ Emp-to-pop	0.0	0.0	-0.1	0.0	0.0	0.1	0.3	187
Emp-to-pop 1995	0.4	0.1	0.2	0.4	0.4	0.5	0.7	187
Δ Wage	0.2	0.2	-0.1	0.1	0.2	0.3	0.8	187
Δ ROB	2.0	1.0	-0.3	1.4	2.0	2.8	4.5	187
Δ ICT	1.4	0.2	0.9	1.2	1.3	1.5	2.0	187
Δ SDB	2.3	0.7	0.7	1.9	2.2	2.6	4.7	187
Δ Imports	1.8	0.7	0.5	1.2	1.9	2.3	3.6	187
Δ Final demand	4.4	6.9	-6.8	-1.2	4.7	7.3	37.2	187
Log Population in 1995	7.1	0.9	3.2	6.6	7.2	7.6	9.3	187

Notes: This table summarizes the descriptive statistics for the independent, dependent and control variables used in the regressions. The change represents the change in the variable of interest between 1995 and 2017.

B Clustering

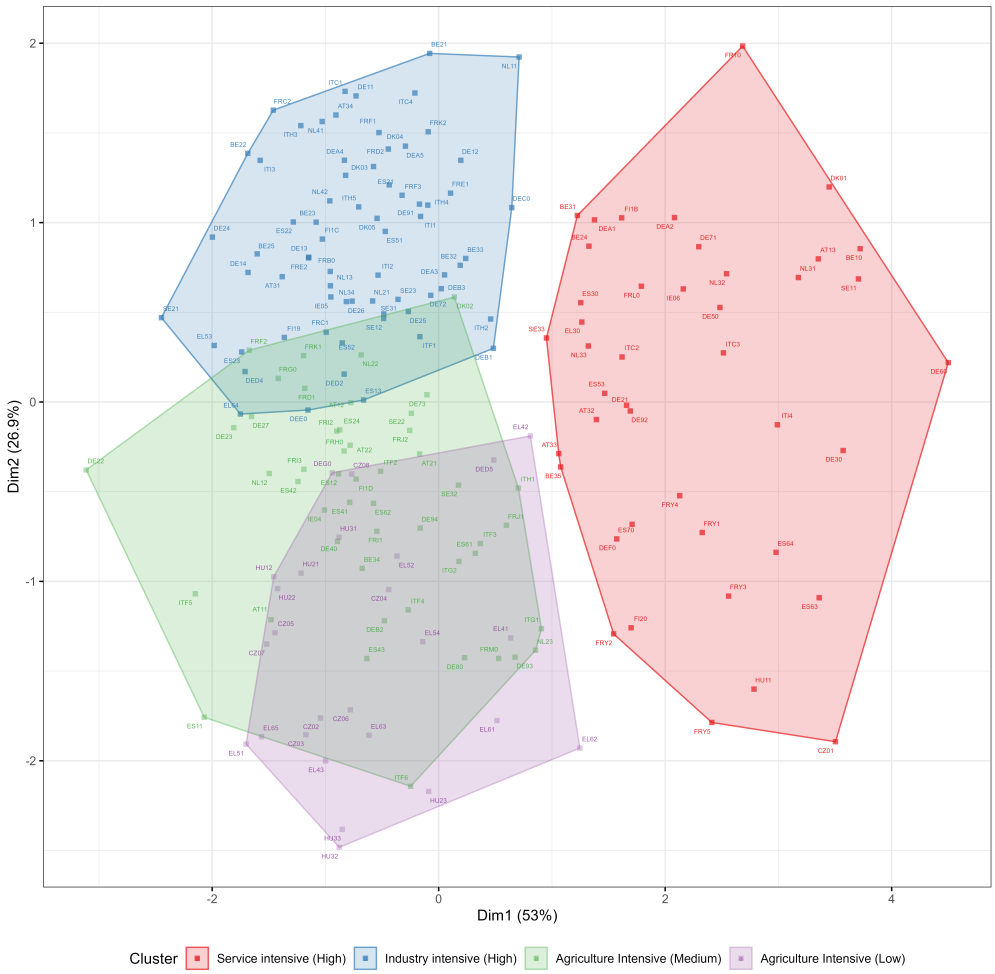
This appendix reports, in Figure B.1, the goodness of fit of the classification of regions using the K-means algorithm. Figure B.2 reports the regional clusters on the first two principal components derived from the K-means.

Figure B.1: Goodness-of-fit



Notes: This figure presents the goodness-of-fit of the K-means clustering for several cluster numbers ranging from 1 to 15. The goodness-of-fit is reported using three metrics: the Within-cluster Sum of Squares (WSS), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

Figure B.2: Regional clusters and the first two principal components



Notes: This figure presents the four clusters on the first two principal components from the K-means algorithm. The set of clustering variables contains the share of the three sectors (i.e. agriculture, industry, and service).

C Regression tables

This appendix reports the estimates of different regression tables. In Table C.1 the results from the first stage are presented. Further, Table C.2 presents the OLS regressions for labor market adjustments to regional technology penetration by cluster.

Table C.1: First stage

	IV Regression - First Stage		
	(1)	(2)	(3)
ROB Exposure (US)	1.47^{***}		
	(0.10)		
ICT Exposure (US)		0.21^{***}	
		(0.05)	
SDB Exposure (US)			0.79^{***}
			(0.13)
R^2	0.53	0.08	0.17
Adj. R^2	0.53	0.07	0.16
Num. obs.	187	187	187

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the first stage of the IV regressions for robots (ROB, column 1), information and communication technologies (ICT, column 2) and software and database (SDB, column 3). The dependent variables represent the ROB, ICT and SDB exposure of European regions in shift-share respectively. ROB, ICT, and SDB Exposure (US) is the instrument variable also constructed as a shift-share with the change in US stock per thousand workers.

Table C.2: Labor Market Adjustments to Technology Penetration at the Cluster Level (OLS)

	OLS Regression - Change in outcome variable (1995-2017)					
	Δ Emp-to-pop. ratio $\times$ 100			Δ Average wage (in log) $\times$ 100		
	(1)	(2)	(3)	(4)	(5)	(6)
Robot						
ROB $\times$ Service intensive (High)	0.44	0.48	1.45	-2.90	-3.22^{*}	-2.36
	(0.49)	(0.50)	(0.93)	(1.82)	(1.85)	(3.47)
ROB $\times$ Industry intensive (High)	0.85^{**}	0.87^{**}	1.49^{**}	-0.96	-1.07	-0.11
	(0.39)	(0.40)	(0.70)	(1.47)	(1.47)	(2.63)
ROB $\times$ Agriculture intensive (Medium)	0.96^{**}	0.94^{**}	1.71^{*}	-1.54	-1.38	-0.09
	(0.47)	(0.48)	(0.88)	(1.76)	(1.77)	(3.27)
ROB $\times$ Agriculture intensive (Low)	1.90	1.95	2.81	2.26	1.88	2.79
	(1.66)	(1.66)	(1.81)	(6.17)	(6.18)	(6.76)
Information and Communication Technology						
ICT $\times$ Service intensive (High)	-0.15	-0.01	-0.62	-6.45	-7.43	-5.34
	(1.54)	(1.56)	(1.70)	(5.75)	(5.81)	(6.35)
ICT $\times$ Industry intensive (High)	1.11	1.32	0.61	-0.67	-2.26	-1.18
	(1.63)	(1.68)	(1.76)	(6.08)	(6.24)	(6.57)
ICT $\times$ Agriculture intensive (Medium)	0.58	0.83	0.20	-5.44	-7.30	-6.38
	(1.91)	(1.96)	(2.02)	(7.10)	(7.30)	(7.53)
ICT $\times$ Agriculture intensive (Low)	15.88^{***}	15.92^{***}	14.85^{***}	3.52	3.22	5.15
	(3.84)	(3.85)	(3.93)	(14.30)	(14.29)	(14.68)
Software and Database						
SDB $\times$ Service intensive (High)	-0.90	-0.75	-0.97	7.28^{***}	6.16^{**}	7.41^{**}
	(0.67)	(0.73)	(0.82)	(2.50)	(2.70)	(3.04)
SDB $\times$ Industry intensive (High)	-1.23	-1.09	-1.24	6.19^{**}	5.17	7.20^{*}
	(0.82)	(0.86)	(1.04)	(3.05)	(3.18)	(3.89)
SDB $\times$ Agriculture intensive (Medium)	-0.72	-0.60	-0.79	7.95^{**}	7.08^{**}	8.99^{**}
	(0.90)	(0.93)	(1.09)	(3.37)	(3.46)	(4.05)
SDB $\times$ Agriculture intensive (Low)	-0.93	-0.65	0.41	-29.49	-31.60	-29.78
	(8.58)	(8.61)	(8.67)	(31.98)	(32.01)	(32.36)
Country FE	✓	✓	✓	✓	✓	✓
Demographics		✓	✓		✓	✓
Covariates			✓			✓
R^2	0.68	0.68	0.68	0.73	0.73	0.73
Adj. R^2	0.62	0.62	0.62	0.68	0.68	0.68
Num. obs.	187	187	187	187	187	187

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the OLS regressions of adjustments of the regional employment-to-population ratio, in Columns (1) to (3), and regional average wage per worker, in Columns (4) to (6), to a change in the regional penetration of robots, information and communication technology, and software and database by cluster. Regional exposure is constructed as a shift–share variable using the sectoral structure of employment in the region in 1995 and the change in the technology stock per thousand workers in the sector within the country. The change is instrumented with the change in the US in the corresponding sector. Clusters are obtained using the K-means algorithm. Clustering variables refer to employment shares in agriculture, industry and services, standardized at the country level, and productivity, expressed as gross value added per worker, standardized over the entire sample. Regions are weighted by their population in 1995. Demographic control includes the population in 1995 in logarithm. Covariates include the change in imports from China (in shift–share) and the change in the real consumption index (in shift–share), both over the same period. Controls include country-fixed effects.

D Robustness Checks

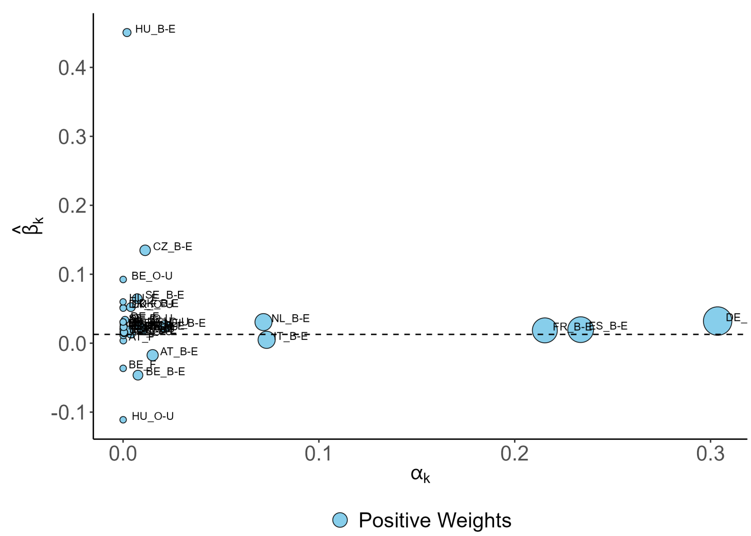
D.1 Rotemberg Weights

Table D.1: Summary of Rotemberg Weights – ROB.

nace	g	alpha	beta	share
DE_B-E	16.555	0.304	0.032	30.362
ES_B-E	10.665	0.234	0.020	23.367
FR_B-E	5.645	0.215	0.019	21.538
IT_B-E	8.286	0.073	0.005	7.331
NL_B-E	10.156	0.072	0.031	7.170

Notes: This table shows the top five country-industries (first column) according to the Rotemberg weights after implementing the decomposition of the IV estimator proposed by Goldsmith-Pinkham et al. (2020). The second column (g_k) represents the country-industry change in robot stock while the third column (alpha α_k) reports the weights, the fourth column (beta) displays the just-identified coefficient estimates (β_k), and the fifth column indicates the proportion that the absolute value of each weight α_k contributes to the total sum of absolute values across all α_k. Control variables include the log of the population in 1995, the change in ICT and SDB, final demand and trade exposure respectively over the period that goes from 1995-2017, and country fixed effects. Regressions are weighted by the population in 1995.

Figure D.1: Heterogeneity in β_k for Robots



Notes: This figure shows the heterogeneity in the estimated effects of robots across different instruments, where each point represents an instrument based on a country-industry share. The y-axis shows the individual estimate of (β_k) for each instrument, while the x-axis plots the corresponding Rotemberg weight (α_k), calculated using the methodology from Goldsmith-Pinkham et al. (2020). The size of each dot reflects the weight of the instrument (larger dots indicate higher weights), and the color indicates whether the estimate is positive (blue) or negative (orange). The horizontal dashed line represents the overall IV estimate of β for robots, as reported in the third column of Panel B in Table 3, but scaled here by dividing by 100.

Table D.2: IV Adjustments to Employment-population-ratio excluding robot largest weights.

	IV Regression - Change in outcome variable (1995-2017)	
	Δ Emp-to-pop. ratio $\times$ 100	Δ Average wage (in log) $\times$ 100
	(1)	(2)
ROB	0.84	-0.46
	(0.84)	(2.68)
ICT	-4.98	4.02
	(3.71)	(11.79)
SDB	5.03^{***}	2.11
	(1.56)	(4.95)
Country FE	✓	✓
Demographics	✓	✓
Covariates	✓	✓
R^2	0.51	0.75
Adj. R^2	0.44	0.71
Num. obs.	149	149

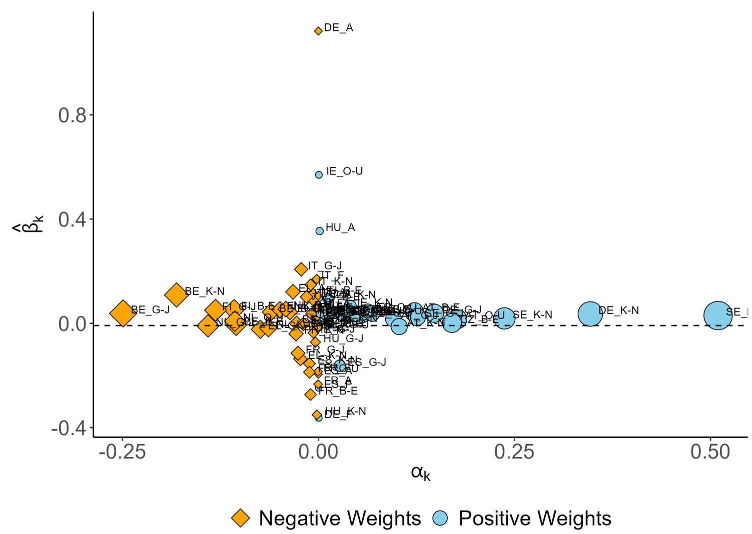
Notes: Standard errors between parentheses. This table summarizes the coefficients from the IV regressions of adjustments of the regional employment-to-population ratio and regional average wage per worker to a change in the regional penetration of robots, information and communication technology, and software and database by cluster. The sample excludes German regions. Regional exposure is constructed as a shift–share variable using the sectoral structure of employment in the region in 1995 and the change in the technology stock per thousand workers in the sector within the country. The change is instrumented with the change in the US in the corresponding sector. Regions are weighted by their population in 1995. Demographic control includes the population in 1995 in logarithm. Covariates include the change in imports from China (in shift–share) and the change in the real consumption index (in shift–share), both over the same period. Controls include country-fixed effects.

Table D.3: Summary of Rotemberg weights – ICT

nace	g	alpha	beta	share
SE_B-E	10.529	0.510	0.030	11.867
DE_K-N	3.833	0.347	0.036	8.072
BE_G-J	4.966	-0.249	0.038	5.800
SE_K-N	12.020	0.237	0.019	5.523
BE_K-N	9.064	-0.181	0.109	4.213

Notes: This table shows the top five country-industries (first column) according to the Rotemberg weights after implementing the decomposition of the IV estimator proposed by Goldsmith-Pinkham et al. (2020). The second column (g_k) represents the country-industry change in robot stock while the third column (alpha α_k) reports the weights, the fourth column (beta) displays the just-identified coefficient estimates (β_k), and the fifth column indicates the proportion that the absolute value of each weight α_k contributes to the total sum of absolute values across all α_k. Control variables include the log of the population in 1995, the change in robots and SDB, final demand and trade exposure respectively over the period that goes from 1995-2017, and country fixed effects. Regressions are weighted by the population in 1995.

Figure D.2: Heterogeneity in β_k for information and communication technologies



Notes: This figure shows the heterogeneity in the estimated effects of ICT across different instruments, where each point represents an instrument based on a country-industry share. The y-axis shows the individual estimate of (β_k) for each instrument, while the x-axis plots the corresponding Rotemberg weight (α_k), calculated using the methodology from Goldsmith-Pinkham et al. (2020). The size of each dot reflects the weight of the instrument (larger dots indicate higher weights), and the color indicates whether the estimate is positive (blue) or negative (orange). The horizontal dashed line represents the overall IV estimate of β for ICT, as reported in the third column of Panel B in Table 3, but scaled here by dividing by 100.

Table D.4: IV Adjustments to Employment-population-ratio excluding ICT largest weights.

	IV Regression - Change in outcome variable (1995-2017)	
	Δ Emp-to-pop. ratio $\times$ 100	Δ Average wage (in log) $\times$ 100
	(1)	(2)
ROB	1.09	0.65
	(0.80)	(2.65)
ICT	-0.38	-10.81
	(3.19)	(10.53)
SDB	2.86^{**}	5.24
	(1.23)	(4.04)
Country FE	✓	✓
Demographics	✓	✓
Covariates	✓	✓
R^2	0.54	0.67
Adj. R^2	0.49	0.63
Num. obs.	179	179

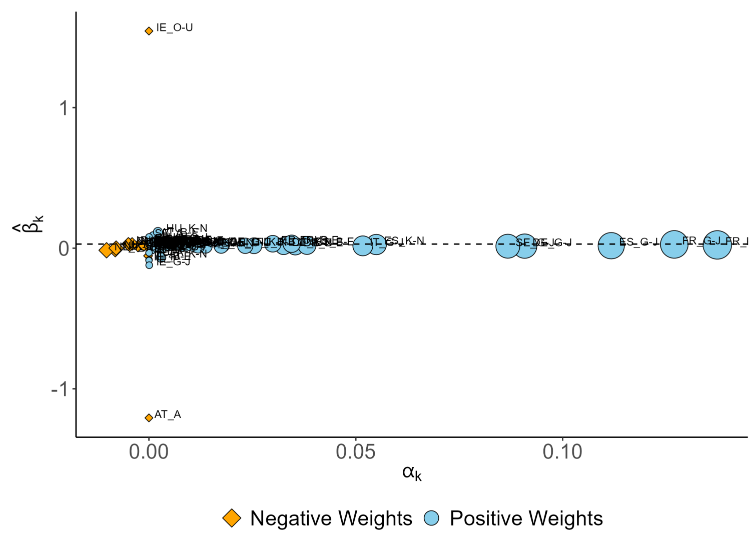
Notes: tandard errors between parentheses. This table summarizes the coefficients from the IV regressions of adjustments of the regional employment-to-population ratio and regional average wage per worker to a change in the regional penetration of robots, information and communication technology, and software and database by cluster. The sample excludes Swedish regions. Regional exposure is constructed as a shift–share variable using the sectoral structure of employment in the region in 1995 and the change in the technology stock per thousand workers in the sector within the country. The change is instrumented with the change in the US in the corresponding sector. Regions are weighted by their population in 1995. Demographic control includes the population in 1995 in logarithm. Covariates include the change in imports from China (in shift–share) and the change in the real consumption index (in shift–share), both over the same period. Controls include country-fixed effects.

Table D.5: Summary of Rotemberg weights – SDB.

nace	g	alpha	beta	share
FR_K-N	11.125	0.137	0.023	12.562
FR_G-J	6.600	0.127	0.027	11.611
ES_G-J	5.717	0.112	0.018	10.217
DE_G-J	2.016	0.091	0.015	8.304
SE_G-J	23.418	0.087	0.014	7.932

Notes: This table shows the top five country-industries (first column) according to the Rotemberg weights after implementing the decomposition of the IV estimator proposed by Goldsmith-Pinkham et al. (2020). The second column (g_k) represents the country-industry change in robot stock while the third column (alpha α_k) reports the weights, the fourth column (beta) displays the just-identified coefficient estimates (β_k), and the fifth column indicates the proportion that the absolute value of each weight α_k contributes to the total sum of absolute values across all α_k. Control variables include the log of the population in 1995, the change in ICT and robots, final demand and trade exposure respectively over the period that goes from 1995-2017, and country fixed effects. Regressions are weighted by the population in 1995.

Figure D.3: Heterogeneity in β_k for software and database



Notes: This figure shows the heterogeneity in the estimated effects of software and databases across different instruments, where each point represents an instrument based on a country-industry share. The y-axis shows the individual estimate of (β_k) for each instrument, while the x-axis plots the corresponding Rotemberg weight (α_k), calculated using the methodology from Goldsmith-Pinkham et al. (2020). The size of each dot reflects the weight of the instrument (larger dots indicate higher weights), and the color indicates whether the estimate is positive (blue) or negative (orange). The horizontal dashed line represents the overall IV estimate of β for SDB, as reported in the third column of Panel B in Table 3, but scaled here by dividing by 100.

Table D.6: IV Adjustments to Employment-population-ratio excluding SDB largest weights.

	IV Regression - Change in outcome variable (1995-2017)	
	Δ Emp-to-pop. ratio $\times$ 100	Δ Average wage (in log) $\times$ 100
	(1)	(2)
ROB	1.11	-5.08^{**}
	(0.92)	(2.49)
ICT	-0.79	-12.01
	(3.26)	(8.80)
SDB	3.24^{**}	3.34
	(1.25)	(3.37)
Country FE	✓	✓
Demographics	✓	✓
Covariates	✓	✓
R^2	0.51	0.79
Adj. R^2	0.45	0.76
Num. obs.	160	160

Notes: tandard errors between parentheses. This table summarizes the coefficients from the IV regressions of adjustments of the regional employment-to-population ratio and regional average wage per worker to a change in the regional penetration of robots, information and communication technology, and software and database by cluster. The sample excludes French regions. Regional exposure is constructed as a shift–share variable using the sectoral structure of employment in the region in 1995 and the change in the technology stock per thousand workers in the sector within the country. The change is instrumented with the change in the US in the corresponding sector. Regions are weighted by their population in 1995. Demographic control includes the population in 1995 in logarithm. Covariates include the change in imports from China (in shift–share) and the change in the real consumption index (in shift–share), both over the same period. Controls include country-fixed effects.