# The diffusion of industrial robots in Europe: regional or country effect?

**Highlights**

- The paper contributes to the debate around the spatial diffusion of innovation, using industrial robots as a proxy of Industry 4.0 transformation
- The map of robots' adoption at the regional level in the 5 largest European economies shows winners and losers in the race for advanced manufacturing
- We explore the relationship between industrial mix and robot adoption also adopting an original measure of relatedness across the regional industrial employment based on a pattern recognition algorithm
- The regression analysis highlights a decisive role of country dummies in explaining the convergence of robot adoption in regions. However, there are important region-specific features which stay significant, namely the level of human capital and the related variety.

**Abstract**

The paper investigates whether the penetration of advanced manufacturing technologies can be better explained at the regional or national level. If regional effects prevail, policy actions would focus on local investments, while if country effects make regional covariates redundant, they should be redirected to more structural reform of the national systems of innovation.

In this respect the contribution is twofold. First, data on acquisitions of industrial robots in the five largest European economies are rescaled at regional levels to draw an essential picture of winners and losers in the robotics race after the 2008 financial crisis. Second, we explain differential of growth rates in robot adoption with (1) traditional measures of industrial variety, (2) an unsupervised machine learning approach classifying a region's industry profile (3) usual determinants of innovation and, thereafter test the robustness of the results when country effects are added. As the main result, we highlight a process of regional convergence in which country-fixed effects hold major explanatory power, although related variety and the number of skilled people are statistically significant regional explanatory factors. We do not discover a specific industry mix associated with the rise of adoption, but we highlight the one associated with its decline.

**Key words**

Robot adoption, National System of Innovation, Industry Mix, Self-Organizing Maps

## 1. Introduction

For those actors able to master the recombination of new digital technologies with traditional manufacturing capabilities, advanced manufacturing technologies (AMT) have become a key competitive advantage by changing business models (Savolainen and Collan, 2020), improving supply chain flexibility and performance (Delic and Eyers, 2020), and fostering sustainable development (Bag et al., 2021). Although since the 1980s the manufacturing sector had already been affected by a first long wave of automation which heavily reduced the percentage of labour, the academic and policy debate has mainly focused on the effect of robots on employment (among others, see Acemoglu and Restrepo, 2018; Chiacchio et al., 2018; MIT Work of the Future, 2019). Less attention has been paid to the new competencies required by the deployment and maintenance of data-intensive technologies (Sivarajah et al., 2017), the institutional resistance to organisational change (Agostini and Filippini, 2019), and especially to the innovative ecosystem in which this transformation takes place.

In the literature on the economics of innovation and economic geography, two complementary spatial approaches have often emerged to assess a major transformation in the mode of production. On the one hand, since the seminal works by Nelson (1993), Freeman (1995), and Lundvall (1998), innovation studies have developed a clear understanding of the role of the national level in fostering technological change, assessing whether technological and industrial policies, the quality of institutions, and large public investments matter more or less than the idiosyncratic characteristics of the regions in which the transformation takes place. The concept of a national system of innovation (NIS) describes organisations and institutions that populate an innovative ecosystem within the country borders and has been successfully employed to explain many radical transitions in the mode of production such as those that occurred in Japan, the USSR, and Korea (Nelson, 1993).

On the other hand, thanks to the contribution of the mature knowledge on agglomeration economies (Neffke et al., 2011; Delgado, 2020) and entrepreneurship (Feldman, 1994, for a seminal contribution; Karlsson and Gråsjö, 2019, for a more recent discussion), scholars stressed the importance of the local and regional level. The main idea is that the adoption of new technologies does not occur in a vacuum (Delgado, 2020), but rests on existing regional characteristics such as local competencies and learning (Morgan, 2007), specialisation (Fritsch and Slavtchev, 2010), the local entrepreneurial ecosystem (Graf, 2006), and existing linkages with other local industries (Midmore et al., 2006) and their relatedness (Boschma, 2017).

The two approaches are not competing, as evidenced by the widespread framework of smart specialisation policies, wherein national innovation policies are implemented at the local level to fit the regional specialisation profile (Foray et al., 2009). It is also evident that for large countries, innovative activity is unevenly distributed across regions and the wealthiest and most developed of them usually drive economic growth at the national level.

A closer look at the literature on NIS can perhaps provide new insights, suggesting that wise and forward-looking governance at the national level is the main driver of profound and successful change. Therefore, in these times of profound transformation, a renewed focus on the national level would not be misplaced. The renewed importance of the state in coordinating national innovative activity towards grand challenges has matched with the rise of mission-oriented policy (Mazzucato, 2016) and even the role of large innovative governmental procurement (Edler and Georghiou, 2007; Guerzoni and Raiteri, 2015).

This paper contributes to understanding the different influence of the two spatial levels in explaining the current transition to AMT. In doing so, we face the same problem discussed before about deriving competing hypotheses from two theories with a profound difference in the way they generate data. Although we acknowledge the feasibility of collecting detailed data at the local level, we also recognize the impossibility of quantitatively measuring the complexity of the NIS.

Therefore, we devise the following empirical strategy. Firstly, we identify robots as a reliable proxy for AMT and provide an original mapping of their stock and growth across 137 regions in 5 European countries. Secondly, we make the most compelling case for the role of regions, selecting two different measures of industrial specialization-diversification as proxies of regional structural factors. Finally, we test whether the above measures are associated with the adoption of industrial robots and whether their significance is robust to the presence of country dummies.

The results provide evidence on which development factors at the regional level explain robot adoption, even when controlling for the national context. Ultimately, we find that country dummies explain a good portion of the variance in the adoption of industrial robots at the local level, but the level of both related variety and human capital still generates a small but statistically significant impact. We also cannot find a typical local industry that most stimulates robot adoption, but we are able to identify the regional pattern associated with its decline. The paper is organised as follows. The next section discusses the case for specialization/diversification and the debate on empirically capturing the regional industry mix that might explain robot adoption at the regional level. Section 3 presents the different levels of our empirical strategy whose results are shown and compared in Section 4. Conclusions follow.

## 2. Regions as driver of adoption: measuring specialization and diversification

The spatial heterogeneity of economic activity has always been an undisputed stylized fact, and the role of local competitive advantages has been a well-investigated topic of research.

The spatial concentration of specific industries is considered the origin of spatially bounded positive externalities and, therefore, has always been studied as a source of localized advantages since Smith (1776) and Marshall (1890). Later, Jacobs (1961) suggested that density and diversity of human activities are also engines of growth, as is the case for cities. Beginning with Glaeser et al. (1992) and Duranton and Puga (2001), a large body of empirical research discussed and compared the effect of specialization advantages, also called Marshall-Arrow-Romer (MAR) externalities, vs. diversification or Jacobs externalities (de Groot et al., 2016). Overall, the industry profile of a region is the idiosyncratic result of a process of economic development that has evolved over time together with the competencies and skills of workers, socio-demographic characteristics, and institutions. In some cases, regional innovation systems can facilitate the adoption of new technologies or almost spontaneously branch into new sectors, while in other regions locked into present economic activities, obstacles prevail and impede the structural change of the economy (Visser and Boschma, 2004).

Regional economic structure has often been analysed in terms of the distinctiveness of its industrial composition, for example, using shift and share analysis, which decomposes differences between values of a chosen variable as observed at the regional and national levels. Despite its limitations, this technique has been widely used in regional studies since the 1960s and it has recently resurged in the analysis of industrial resilience (see for example Martin et al., 2016).

The seminal contribution by Frenken et al. (2007) on related variety (RV) and unrelated variety (UV) introduced an extension and further specification on how agglomeration economies work: in order for the advantages of diversity to fully display, not only spatial concentration does matter, but also the knowledge produced and exchanged at the local level has to be somehow related. Moreover, as pointed out by Content and Frenken (2016), the type of diversification can also have explanatory power on innovation, knowledge, and entrepreneurship, all of which are mediating factors that ultimately lead to growth.

The large body of empirical evidence accumulated on UV and RV makes these two measures able to represent the local advantages of regions vis-à-vis the possibility of deep technological transformation. Along this line, Castaldi et al. (2015) find that RV favours incremental innovation and UV creates a more fertile environment for radical innovation. In a dynamic perspective, Zabala-Iturriagagoitia et al. (2020) claim that UV and RV coexist, although the former is more effective in periods of economic expansion, while the latter provides better results in periods of crisis. According to Cortinovis & van Oort (2015), RV is limited within specific sectors and, therefore, regions with a higher UV are able to transform their economy in times of crisis, because they can rely on a sort of portfolio effect. In a recent paper, Xiao et al. (2018) find that both RV and UV are crucial to explain resilience in the short term. For this reason, if the case of robots were consistent with this literature, we would expect both indicators to be significant in explaining the growth of adoption and a higher level of UV to be an advantage in the post-2008 crisis.

From an empirical perspective, Content and Frenken (2016) wonder what the best method to capture RV is and what other dimensions could contribute to grasping relatedness. While the UV/RV approach has achieved remarkable results in capturing agglomeration economies embedded in the idiosyncratic industry profile of a region, it also causes a loss of information since it does not provide any hint on the sectors behind the level of diversification.

In the challenge of overcoming this limitation, alternative measures of local industry mix have emerged exploiting advanced pattern recognition techniques and neural networks (Bação et al., 2005). For example, Carlei and Nuccio (2014) apply Self-Organising Maps (SOM) (Kohonen, 1990) to find similarities and differences across regional industrial clusters based on the local distribution of employment over different industries. While industrial proximity has usually been measured in terms of input similarity (Frenken et al., 2007), co-occurrences of trade activities (Boschma and Iammarino, 2009) or skill-relatedness (Neffke and Henning, 2013), this approach adopts the employment composition of the local economy as a proxy for human capital, assuming that the number of employees in one sector implicitly accounts for a set of competences and capabilities.

Consistently with a policy perspective, SOM capture relatedness indirectly through the regional similarity and derive industry mix *ex-post* from data. This last measure is also consistent with the idea behind the Atlas of Economic Complexity (Hausmann et al., 2014; Neffke et al., 2017), which is probably the most successful attempt to measure the progressive transformation of economies from a low-tech specialization into advanced and diversified successful economies. By mapping and visualizing the pattern of relatedness among industry, *where "relatedness is not about over-specialization"* but *"about understanding the unique paths that lead to diversification"*

(Hidalgo et al., 2018, 454) such an approach shows both theoretically and empirically that global trend to diversification into new industries is not random but follows specific paths. Accordingly, Pagliacci et al. (2019) show that a clustering approach aimed to identify macro-regions can be very effective for designing and implementing innovation policies and for greater cohesion and competitiveness across larger EU spaces. Such a meso-level allows to address common challenges and strengthen complementarities within neighbouring regions in different countries, but also overcomes the dichotomy specialization vs. diversification (Caragliu et al., 2016).

## 3. Empirical strategy

Our empirical analysis draws from two data sources. The IFR (2017) database provides industry disaggregated data on the annual number of robots delivered to countries from 1993 to 2015, where robots are defined according to the International Organization for Standardization (ISO). The EUROSTAT SBS database provides us with yearly data on regional number of employees and firms by industry over 20 years (1995-2015). Data on the regional number of firms[1] is used to calculate the regional robot density index. Data on the number of employees used to build the industry mix is reliable only starting from 2001 and changes in NACE classification do not allow a full data crosswalk before and after 2008.

As IFR and EUROSTAT data use different industry classifications, to allocate robots to regions we had to harmonize the various sources of data.[2] Out of the 18 IFR industries, we are able to match the following 16:[3] mining and quarrying, all manufacturing industries (11 industries), utilities, construction, “P-Education/research/development” and “90-All other non-manufacturing branches”.

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[1] EUROSTAT SBS provides data on the number of local units. Following EUROSTAT SBS definition of local unit (EUROSTAT SBS – METADATA), we use the terms firm and local unit interchangeably.

[2] More details are available in the Appendix

[3] The two IFR industries excluded are “A-B-Agriculture, forestry, fishing” and “99-Unspecified”. On average, these two industries account for 7.6% of annual delivered robots.

The last two industries are aggregated under the service industry giving 15 sectors in total for the analysis. The adopted correspondence table is shown in the Appendix (Table A1).

We focus on 137 NUTS 2 regions (Eurostat, 2011) of five largest European countries,[4] namely France, Germany, Italy, Spain and the UK. After matching the two databases, we compute the annual stock of robots using the perpetual inventory method (PIM) on robot deliveries data, assuming a depreciation rate of 10%. We use the IFR's estimated value of the robot stock for 1993 as the initial value of the stock in our PIM (Graetz and Michaels, 2018).

Though we are unable to construct a panel dataset due to missing data, necessitating the averaging of employee numbers over time in certain sectors, we maintain a dynamic perspective. We do so by contrasting the positive economic cycle between 2001 and 2007 (Period I) with the subsequent recovery phase from 2013 to 2015 (Period II), following the downturn of the financial crisis (2008-2012). We believe this strategy offers additional advantages, as changes in industrial structure occur gradually and are challenging to discern with a yearly panel approach. Instead, our approach allows us to reduce the number of missing values by utilizing a multi-year average and comparing two distinctive moments, divided by the crisis, which surely impacted the industrial structure of the regions differently. We test whether specific regional industry mix explains robot adoption and whether this effect is significant after the introduction of country dummies. Specifically, we estimate a linear model:

$$ROB\_Growth_{pII-pI} = \alpha X_{pI} + \beta Z + \varepsilon \qquad [1]$$

where ROB_growth is the regional growth rate between the first (*pI*) and second period (*pII*) in the robot stock per capita, X is a matrix containing a set of variables capturing regional characteristics

[4] 141 NUTS 2 regions are distributed by country in the following way: 26 French, 38 German, 19 Spanish, 21 Italian, and 37 UK regions. Because of lack of data we excluded the 4 extra European French regions in South America, so the analysis is based on 137 regions.

(level of RV and UV, dummies for the SOM clusters, other regional controls) measured using data for the first period, Z is a matrix containing country dummy variables and ε is the error term. In the next paragraphs, we present respectively the proxy variables employed in our estimation.

### 3.1. Dependent variable

The stocks of robots aggregated by country and industry are allocated to the 137 regions using the number of firms per industry as in the following equation:

$$Robot\ stock_{i,t} = \sum_{j=1}^{15} \frac{N\ Firm_{j,i,t}}{National\ N\ Firm_{j,t}} * National\ Robot\ stock_{j,t} \qquad [2]$$

where $Robot\ stock_{i,t}$ is the stock of robots in region *i* at year *t*; $N\ Firm_{j,i,\ t}$ and $National\ N\ Firm_{j,t}$ are, respectively, the regional and national number of firms in industry *j* at year *t* ; and $National\ Robot\ stock_{j,i,\ t}$ is the national stock of robots in industry *j* at year *t*. The regional indexes of robot density used in the following analysis are computed as the ratio between the stocks of robots and population (thousands of inhabitants).[5]

The methodology adopted to compute the regional indexes of robot density is similar to that used in studies analysing the effects on regional employment of the exposure to robots (Acemoglu, and Restrepo, 2018; Chiacchio et al., 2018; Dauth et al., 2017). Basically, in these studies the regional exposure (adoption) of robots in an industry is proportional to the regional employment in that industry. Both methodologies assume that the distribution of robots within an industry is uniform across all regions within a country conditional on firm shares (or employment shares) in each region-industry. We are aware that our measure of robot stock might be affected by cross-regional differences in firm characteristics such as firm size and firm productivity. To account for these differences, we compute an additional measure of robot stock using data on regional value added. Regional differences in terms of industry value added might reasonably reflect regional differences

[5] Data on annual regional population are provided by EUROSTAT.

in firms' market shares and productivity levels. The availability of data (from national statistical offices) on regional industry value added, especially for manufacturing industries, limits our analysis to Italy and the UK. The correlation between the regional robot stocks computed using alternatively the regional share of value added and the share of firms is very high (about 0.86) and there are no statistical differences between the mean values of the two measures of regional robot stocks. Based on these descriptive statistics, we can safely assume that the robot stocks computed using data on the regional number of firms are not severely affected by cross-regional differences in firm characteristics.

### 3.2. Independent variables

In this paper we measure spatial concentration and industrial specialization using two sets of indicators to model the possible regional advantages in the adoption of industrial robots and a set of variables to control for economic development.

Following Caragliu et al. (2016), we use the available employment data to calculate RV and UV, where UV is the entropy of one-digit distribution and RV is the weighted sum of the entropy indicator at the two-digit level within each one-digit class:

$$UV = \sum_{g=1}^{G} P_g \frac{1}{P_g} \quad [3]$$

with $P_g$ = share of employment in the 1-digit sector *g* and

$$RV = \sum_{g=1}^{G} P_g H_g \text{, where } H_g = \sum_{i \in g} \frac{P_i}{P_g} \frac{1}{\frac{P_i}{P_g}} \quad [4]$$

with $P_i$ = share of employment in the 2-digit sector *i*.

Our measure of RV assumes that two industries are more related to each other when both industries share the same one-digit class. By contrast, UV measures the extent to which a region is diversified in different one-digit industries.[6]

As mentioned, we calculate an alternative measure of industrial specialization and diversification using SOM similarity to cluster regions. The SOM is a neural network that represents a nonlinear transformation from a continuous input space to a spatially discrete output space, i.e., SOM aggregate regions using specific regional features as input and then, project clusters on a 2-dimensional space which maps the proximity among the same clusters. The input data is a matrix X, whose entries $x_{i,j}$ are i-samples (regions) and j-features (industries). Consistently with the available data, each scalar in our matrix $X_{i,j}$ measures the number of employees in each $i = 1 \ldots n$ of the 137 European regions (NUTS 2) per $j = 1 \ldots m$ industries (2-digits). Although it would be possible to show the temporal evolution of the industry profile before and after the 2008 financial crisis, for the specific purpose of this paper we only run SOM in the Period I. We trained a features map composed of nine different macro-regional patterns (3*3 spatially ordered neurons)[7] which have clustered all the 137 European regions. The output of the SOM is a topological map (also called feature map) which classifies regions and provides the underlying profile of specialization which characterizes each cluster.

### 3.3. Regional controls

[6] Beyond the use of the hierarchical structure of the industry classifications, other two main approaches are used in the literature to measure relatedness (Neffke and Henning, 2013). The first one is a co-occurrence-based approach which, for example, considers the co-presence of industries in the regions' export portfolio. The other one is a resource similarity based approach which considers the closeness between industries in terms of employed resources (e.g. occupation profiles). Each of these approaches has advantages and disadvantages and it is not yet established the appropriateness of them in the various contexts of analysis. Due to data limitation, we consider the approach based on the hierarchy of industry classifications. However, this approach is the most used in literature both for the availability of data and for the simplicity of calculation.

[7] The size of the final feature map is determined by a trade-off between compressing information into few patterns (clustering) and topological accuracy: larger map sizes result in more detailed patterns; smaller map sizes result in more general patterns.

Eventually, to make the case for the role of the region even more compelling we add a battery of controls, which have been identified in the literature as key determinants for a successful economic development. Existing literature argues that human capital (among others, Benhabib & Spiegel, 1994; Nelson & Phelps, 1966) and R&D investments (Cohen and Levinthal, 1990; Griffith et al., 2004) are important channels in facilitating technology adoption at firm and aggregated level. Therefore, we control for the regions' absorptive capacity using three lagged variables: the shares of high skilled people (HK), i.e. the shares of population aged 25-64 with a tertiary education[8]; the R&D per capita expenditures (RDpc); the number of EPO patents per capita[9] (PATpc).[10] The regional GDP per capita (GDPpc) is included to control for the overall historical level of economic development. Eventually, since starting condition matters, we add the log of Robot stock in the first period of the analysis (Log_ROBOTpc). As usually performed in growth regression analysis also at the regional level (Sala-i-Martin 1996; Arbia and Piras, 2005; Young et. Al., 2008), a negative significant effect of this variable can be interpreted as evidence for a process of convergence between regions, and divergence otherwise.

## 4. Results

### 4.1. Mapping industrial robots in major European economies

In 2015 the five countries considered in this paper accounted for 75% of the European robot acquisition although this figure was 10% higher in the years before the economic crisis (Table 1). Germany alone retains 42% of the whole European robot stock. While Germany and Spain have maintained their market shares over time, Italian, France and especially the UK have shown much lower growth rates and reduced their shares. Even at the regional level concentration is remarkable

[8] Tertiary education is defined according to the International Standard Classification of Education (ISCED) levels 5, 6, 7 and 8 (short-cycle tertiary education, bachelor's or equivalent level, master's or equivalent level, doctoral or equivalent level).
[9] Patents are assigned to regions using the inventors' addresses (see e.g.: Cappelli and Montobbio, 2016).
[10] To construct these variables, we use EUROSTAT REGIO data, with the exception of patent data for which we rely on ICRIOS-PATSTAT database on EPO patent applications (Coffano and Tarasconi, 2014).

(Table 2) Top 20 regions absorb almost 50% of continental stock and 13 of them are in Germany, 4 in Italy, 2 in France, 1 in Spain and none in the UK.

Table 1 about here

Table 2 about here

Robot density at the country level shows a typically negative relation between stock and growth which seems to suggest a possible long-term convergence in the adoption of automation technologies. Plotting the number of industrial robots for all 137 regions considered (Figure 1) visually confirms the negative relation between stock and growth and a strong country effect. British regions are very concentrated in the low-stock and low-growth area of the plot although Scotland has the two regions with the highest growth rate in the sample. Spanish regions are very dispersed: Navarra has very good stock and a strong growth rate while in the Canarias both indicators are low. Italy is relatively well equipped with robots but on the whole shows decreasing growth rates of adoption. Germany has got the highest within-country heterogeneity. Some German regions like Dresden and Thüringen combine a good level of robot penetration with a sustained growth. Other regions like Stuttgart and Chemnitz are endowed with a very high stock but have not grown between the two periods. City-states like Berlin and Hamburg started from a very low stock and showed a moderate-high growth rate of robots. The within- and between country heterogeneity is more clearly visible in Figures 2 and 3, which respectively plot the average robot stock and average growth between Period I and Period II in the different regions.

These maps suggest two general results. First, despite heavy within-country disparities, regional economies seem to be affected by national policies, which apply to both more- and less economically advanced regions. Robot stock is quite remarkable in the whole of Germany and, to a lesser extent in some Italian regions, while growth rates tend to be higher again in Germany and in some Spanish and British regions, while very low in France and Italy. Second, we can easily group areas in 4 classes. South-of-Germany and Northern Italy are the *leaders* in robot adoption, however while the former is *staying-ahead*, the latter is *falling behind*. There is a group of regions in Scotland, Spain and above all Eastern Germany which is *catching-up*, while French regions are *staying-behind*. In conclusion we can observe some emerging trends at the country level despite the strong regional variation. In the remainder of the paper, we try to understand to which extent this regional heterogeneity can be explained by specific region characteristics such as the initial condition, the prevailing agglomeration economies, the local industry profile, the level of technological knowledge and human capital, or conversely if country fixed effects have a larger explanatory power.

Figure 1 about here

Figure 2a and 2b about here

Figure 3 about here

### 4.2. Variety and industry mix of major European economies

Comparing these two measures respectively in the Period I and II we observe that the UV has grown substantially and has particularly concentrated in a few regions (Figure 4a and 4b). While in Period I was quite uniformly distributed over European regions, in Period II we observe very high values in the UK and in the major metropolitan areas including all capital cities, but also in some Mediterranean regions of Italy, France and Spain. The increase in UV after a crisis is not surprising, as its correlation with a recovery phase has already been hypothesized and partially documented in the literature, as seen in Zabala-Iturriagagoitia et al. (2020) and Kiss et al. (2018).
Although also RV has increased over time, the map of regions seems more stable and shows a lower variance of values (Figures 5a and 5b). The upper range values are particularly concentrated around the Alps, namely in Southern Germany, Northern and Central Italy, and to a lesser extent in a few regions in Eastern Spain, Northern France and Central England.

Figure 4a and 4b about here

Figure 5a and 5b about here

When plotting these patterns on a geographical map (Figure 7) we are not surprised to find a geographical contiguity of regions within the same pattern, but beyond the strictly national borders. Before any specific consideration on the nature of the patterns, this result highlights the effectiveness of the SOM approach to track the uneven, yet not random diffusion of industrial specialization since topological proximity on the features map mirrors spatial agglomeration of regional economic structures. Furthermore, the SOM approach allows an *ex-post* exploration of the factors that led to these patterns by analysing the relative importance of each industry[11].

In the following paragraphs we present a taxonomy of Europeans regions and some key traits of each pattern identified in Period I (Table 3**)**. Beginning from the top-right of the SOM feature map (Figure 6) we find nine macro-regional patterns based on different manufacturing mix (7, and 8). Predominantly concentrated in Southern Germany, pattern 8 is built on a variety of purely manufacturing sectors (e.g. medical and electrical equipment, machineries, motor vehicles), while pattern 9 includes Northern Italy and North-West of France and is more specialized on labour intensive manufacturing like food and leather transformation.

Table 3 about here

On the top-left side of the feature map we find two different urban-based models: pattern 4 (capital cities and mostly South of England regions) thrives on pure professional and business services, while pattern 7 (Paris and the major German cities) has combined telecommunication with some strategic manufacturing, namely chemicals and motor vehicles. The bottom-right of the feature map

[11] For each industry $j$ the SOM releases a codebook, i.e. the convergence value between 0 and 1 of the weight $W_v$, by which the SOM algorithm has reconstructed the relationships between the given industry and all the others. Figure A1 in the Appendix shows the relative importance of some features (industries) for each pattern. In order to select only those features which are relevant for each pattern, first, we extract those industries whose codebook variance is higher than the average value and, second, we choose the outlier values (see Table A2 in the Appendix)

identifies Mediterranean and Atlantic regions (pattern 6) and South of Spain (pattern 3). They are both characterized by low value added and local industries, mainly construction, mining and -particularly for pattern 6 the agri-food value chain.

Both patterns in the bottom-left of the feature map (1 and 2) are tourism-based economies, but only the latter is specialised and covers the most popular European destinations from the Canary Islands to Alps, while the latter include regions in marginal tourism areas, mostly in the rural UK. Eventually, in the middle of the feature map we find pattern 5 (East-Germany and English midlands) which balances somehow divergent urban, rural and manufacturing features and presents a specific sectoral strength in retail and utilities.

Figure 6 about here

Figure 7 about here

As we did for RV and UV, after classifying European regions in patterns of macro-regions and exploring their difference in term of relatedness of their industrial composition, we can eventually evaluate the extent to which the industry mix is a possible antecedent to the penetration of industrial robots, and, thus, correlates with an increasing diffusion of robots.

Figure 8 shows the boxplot of the growth of robots for the nine SOM patterns and small dots are the jittered observations. Visually, the growth of robots is positive for all groups, but very small for pattern 6 and 9, and high for pattern 3. The statistical analysis of the variance corroborates this view. The ANOVA test rejects the hypothesis that the mean of the growth of robots is the same for all groups, at the 0.001% level of significance. Specifically, the Tukey Honest Significant Differences Test for pairwise comparison shows pattern 9 has smaller mean of growth than any other one and that pattern 6 has a smaller mean than pattern 3. The remaining pairwise comparisons do not show any statistical significance difference.

Figure 8 about here

The descriptive statistics of the variables used in the regression analysis are provided in Table 4.

Table 4 about here

### 4.3. Regions and countries in the adoption of industrial robots

We run the OLS regression adding controls stepwise, introducing before regional characteristics and, only at the end, country dummies. (Table **5)**. Model 1 shows the significance effect of the SOM patterns alone in explaining the growth of robots and confirms the lowest growth rate of robots for pattern 9 as expected from the ANOVA analysis. We add stepwise all the controls in models from 1 to 5. The effect of the SOM fades almost completely away, when we add country dummies (Model 5). As already shown in Figure 1 with regions, also the SOM patterns exhibit a strong country specificity, although it is worth recalling they have been generated with no information on the country. Pattern 2 and 3 remain significant in all specifications with a positive effect with respect to pattern 9, corroborating the evidence that the once lively manufacturing system in France and Italy is falling behind in terms of per capita robot adoption, while the Spanish manufacturing core is eventually catching up.

This dynamic between the decline of former large robot adopters and the catching-up of some other regions explains both the significance and the negative sign of the level of the initial stock of robots per capita and produces evidence of a convergence process among the regions analysed in the paper. RV is also significant and with a positive sign, once again validating the idea that the ability of regions to leverage on different, but related types of industries have a positive effect on adopting innovation in general and, specifically, industrial robots. UV, a hallmark of highly diversified geographical units like cities, does not exhibit a positive correlation with robot adoption. Among the remaining controls, only the share of skilled people is significant, while other proxies for the knowledge intensity of the regions are not.

This final exercise provides an interesting portrait of robot adoption in these selected EU regions. There is a strong country effect that likely captures institutional and policy variables. For example, policies for Industry 4.0 occurred everywhere, but in some countries have been massive (Klitou et Al., 2017; Perani et Al., 2019). The French and Italian manufacturing macro-region shows a persistent decline beyond the country effect, which should warn local policy makers. Overall, the bad performance of these regions is partly compensated by the catching up of some others, that however remain still far from the absolute level of robots tout-court and robot per capita of declining countries. Thus, at the European level, policy makers should worry about an average decline in the exploitation of industrial robots, and thus related technologies of advanced manufacturing: at the moment, it seems that only the German manufacturing system has both the absolute size to compete in the global market and a growth in robot adoption.

Furthermore, combining the regression analysis with SOM exercise (Table 3), which elicits the characteristics of the nine patterns, we can conclude that although no specific combination of sectors grants a safe transition from traditional manufacturing to the new paradigm, however, one pattern is not delivering as one can expect. In fact, Northern Italian and North-West French regions (Pattern 9) are still characterized by labour intensive traditional manufacturing sectors such as "Tanning and dressing of leather", "Manufacture of luggage, handbags, saddlery, harness and footwear" and "manufacture of food product" vis à vis the catching-up Spanish core (Pattern 3) shows an increasing role of more AMT products such as "Computer and related activities" and "Manufacture of radio, television and communication", and the staying-ahead German manufacturing system (Pattern 8) thrives on new areas of high-knowledge intensity such as "Manufacturing of medical, precision and optical instruments" and "Electrical machineries".

Table 5 about here

## Conclusions

This paper describes the regional diffusion of industrial robots in the five largest European economies comparing the regional antecedents of robots with the national fixed-effect before and after the 2008 financial crisis. Not surprisingly, the regional map of the level of robots' penetration in Europe shows a stunning concentration in the core manufacturing regions of Germany and Italy, while growth rates reward only Germany and some more peripherical European regions, thus excluding the traditional manufacturing clusters in Italy, France, and UK. Overall, despite the heterogeneity of penetration of industrial robots, we observe a process of convergence. The only macro-region both very well-equipped with advanced automation and on a pattern of growth is Southern Germany with its variety of integrated manufacturing industries. Northern Italy had accumulated a good robot stock, but showed a declining growth rate, while French manufacturing regions are late with stock and unable to increase the existing levels. We find three industrial patterns on a good path of robot growth: the manufacturing regions in the English Midlands and Eastern Germany, the capital cities-regions, and some sparse regions in Spain, Italy and Scotland, which yet started from a very low provision of robots. In other words, the present robots transformation is showing few regions maintaining their lead, few others catching-up while some former leaders are now falling-behind.

Qualitatively it is difficult to elicit whether the prevailing effect explaining different growth rate in the stock of industrial robots is a regional phenomenon or conversely, the country effect plays an important role. However, we believe that the understanding of the level of granularity associated with the largest explanatory power is a pivotal information for the policy maker. Indeed, regional effects, if prevailing, call for more focus on local investments. On the contrary, if country effects make regional covariates redundant, policy measures should be redirected to more structural reform of the NIS, grand national challenges, and close monitoring on the national environment which might harm or speed-up the transition.

Independent variables include the traditional measures of RV and UV and a complexity measure of the regional industry mix based on SOM, which clusters European regions in archetypical industry patterns. The SOM approach has two major advantages. First, it captures differences in RV and UV by combining the two indicators and freeing them from their dependence on tiers of industrial classification. Second, by classifying regions on the basis of non-linear interactions of employment shares, it is more effective than a mere linear clustering to suggest which different industry profiles explain a different value of RV and UV and, therefore, allows for a sector specific analysis of patterns.

We find mixed results. The regression analysis highlights a decisive role of country dummies in explaining the convergence of robot adoption in regions. However, there are important region-specific features which stay significant, namely the level of human capital and the RV. Although UV is considered by the literature relevant for radical innovation and in post crisis periods, we observed any significant effect.

After controlling of country-effect, regional patters fail in characterizing which industry mix awards a high adoption rate of robots. This is good news for the policy makers: the industrial transformation in place does not necessarily imply a path-dependency from initial conditions. We do find one SOM pattern which hinder the transition to a more intense use of industrial robots: the French and Italian manufacturing regions, which did not diversify in end-products, nor processes related to AMT, but remained attached to traditional sectors, show a small or negative growth of robot adoption. For France and Italy, this implies a very pessimistic outlook on the industrial transformation since not only do they exhibit a negative country effect in the adoption of robots when compared with Germany, but also regional characteristics do not manage to compensate for it. These results should be interpreted with caution due to some limitations in this study. The most important limitation pertains to the data. On the one hand, we believe that improved data provision could expand the sample size, both temporally and geographically, including more countries. Better data could also allow for greater temporal and spatial granularity. A longer time series could enable a better appreciation of changes in the structure with the SOM approach. When data at least until 2025 becomes available, it will also be possible to compare the structural changes of the 2008 financial crisis with those of the more recent COVID-19 pandemic. Moreover, having a broader geographical scope would not only enrich the analysis but also better leverage the power of unsupervised training in SOMs.

Finally, a key assumption in our study is how we have reported IFR data at the regional level and managed the transitions between industrial classifications that have changed over time. These classifications must then be requalified at the technological level for robots.

Despite these limitations, this is a quantitative analysis that, at an aggregate level, certainly captures the transformation as described qualitatively. Furthermore, the contribution of SOM shows region by region how the industrial mix is transforming and provides valuable information for policymakers

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## Tables

**Table 1.** Stock of robots adoption in the five major European countries

| Country | *2001* | | *2007* | | *2015* | | *Growth rate 2001-2015* |
|---|---|---|---|---|---|---|---|
| | ***Number*** | *%* | ***Number*** | *%* | ***Number*** | *%* | *%* |
| DE-Germany | 99195 | 43% | 139980 | 43% | 182632 | 42% | 46% |
| ES-Spain | 16378 | 7% | 27473 | 8% | 29718 | 7% | 45% |
| FR-France | 22753 | 10% | 33462 | 10% | 32161 | 7% | 29% |
| IT-Italy | 43911 | 19% | 61589 | 19% | 61282 | 14% | 28% |
| UK-United Kingdom | 13411 | 6% | 15340 | 5% | 17469 | 4% | 23% |
| 5 countries | 195648 | 84% | 277844 | 84% | 323262 | 75% | 65% |
| EU-EUROPE | 232603 | 100% | 328890 | 100% | 433303 | 100% | 46% |

**Table 2.** Stock of robots adoption in the top European regions

| **Ranking** | **NUTS2 code** | ***NUTS2 label*** | ***Average Stock 2013-2015*** |
|---|---|---|---|
| 1 | DE11 | Stuttgart | 10160.64 |
| 2 | ITC4 | Lombardia | 9003.558 |
| 3 | DE21 | Oberbayern | 6800.09 |
| 4 | DEA1 | Düsseldorf | 6303.31 |
| 5 | DEG0 | Thüringen | 5698.031 |
| 6 | DEA5 | Arnsberg | 5526.81 |
| 7 | DE12 | Karlsruhe | 5477.54 |
| 8 | ITC1 | Piemonte | 5084.788 |
| 9 | DED2 | Dresden | 4922.9 |
| 10 | DEA2 | Köln | 4786.401 |
| 11 | ITH5 | Emilia-Romagna | 4466.516 |
| 12 | ITH3 | Veneto | 4455.11 |
| 13 | ES51 | Cataluña | 4360.845 |
| 14 | FR10 | Île de France | 4341.187 |
| 15 | DE71 | Darmstadt | 4237.546 |
| 16 | DE13 | Freiburg | 4130.455 |

| | | | |
|---|---|---|---|
| 17 | DE14 | Tübingen | 3940.298 |
| 18 | DE94 | Weser-Ems | 3690.593 |
| 19 | DE27 | Schwaben | 3386.578 |
| 20 | FR71 | Rhône-Alpes | 3168.091 |

**Table 3.** A taxonomy of regions in the five larger European economies in Period I

| SOM 2001-07 | Macro-Regions | SOM distinctive industries | SOM Outliers | Industry mix |
|---|---|---|---|---|
| 1 | Rural UK | Hotels and restaurants; Retail | - | Mass Services, Small tourism; Low Variety |
| 2 | Advanced tourism regions | Construction; Hotels and restaurants | Hotels and restaurants, Manufacture of radio, television and communication equipment Water transport | Pure tourism-related activities |
| 3 | Spanish core | Construction | Computer and related activities Construction; Manufacture of radio, television and communication equipment and apparatus; Mining of metal ores | Mining; Construction |
| 4 | Capital Cities | Computer programming; Other Businesses | Activities auxiliary to financial intermediation Computer and related activities; Other business activities; Research and development | KIBS, no manufacturing; Very high Variety |
| 5 | Eastern Germany and England | Retail | Collection, purification and distribution of water | Mass Services; No specialization |
| 6 | Mediterranean & Atlantic regions | Food and beverage; Construction of buildings | Mining of metal ores Mining of uranium and thorium ores | Food and Beverage; Construction |
| 7 | German cities, Paris | Post and Telecommunications; Other Businesses Computer programming; Manufacture of chemicals and chemical products; Manufacture of motor vehicles | Computer and related activities; Manufacture of chemicals and chemical products Post and telecommunications; Supporting and auxiliary transport activities; activities of travel agencies | KIBS; Specialized manufacturing; Very high Variety |
| 8 | Southern German manufacturing | Manufacture of fabricated metal products; Manufacture of electrical equipment Manufacture of machinery and equipment; Manufacture of motor vehicles | Manufacture of basic metals Manufacture of electrical machinery and apparatus; Manufacture of machinery and equipment; Manufacture of medical, precision and optical instruments, watches and clocks; Manufacture of motor vehicles, trailers and semi-trailers | Pure Manufacturing |
| 9 | French & Italian manufacturing | Manufacture of food products; Manufacture of fabricated metal products; Manufacture of machinery and equipment | Manufacture of fabricated metal products; Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear | Labour Intensive Manufacturing |

**Table 4.** Descriptive statistics (N=137)

| *Variable* | *Min* | *Max* | *Mean* | *St.Dev.* | *Description* |
|---|---|---|---|---|---|
| ROB_growth | -0.354 | 2.28 | 0.379 | 0.472 | Log Difference Period II-I |
| Log_ROBOTpc | 0.28 | 5.307 | 3.466 | 0.98 | Log average Period I |
| UV | 1.972 | 2.719 | 2.424 | 0.129 | Unrelated variety av. 2001-02 |
| RV | 0.55 | 2.35 | 1.673 | 0.319 | Related variety average 2001-02 |
| HK | 9.243 | 45.114 | 23.177 | 7.223 | Share of workers with higher education. Average 2001-07 |
| RDpc | 0.018 | 1.908 | 0.321 | 0.287 | Expenditure in Euros per thousand inhabitants. Average 2001-07 |
| PATpc | 0 | 0.684 | 0.128 | 0.135 | Patents per thousand inhabitants. Average 2001-07 |
| GDPpc | 13.663 | 88.77 | 26.807 | 8.311 | Log Average in Period I |

Note: country and SOM dummies are not reported for the sake of clarity

**Table 5.** Determinants of robot growth adoption - OLS estimates
Dependent variable: robot growth between Period I and II

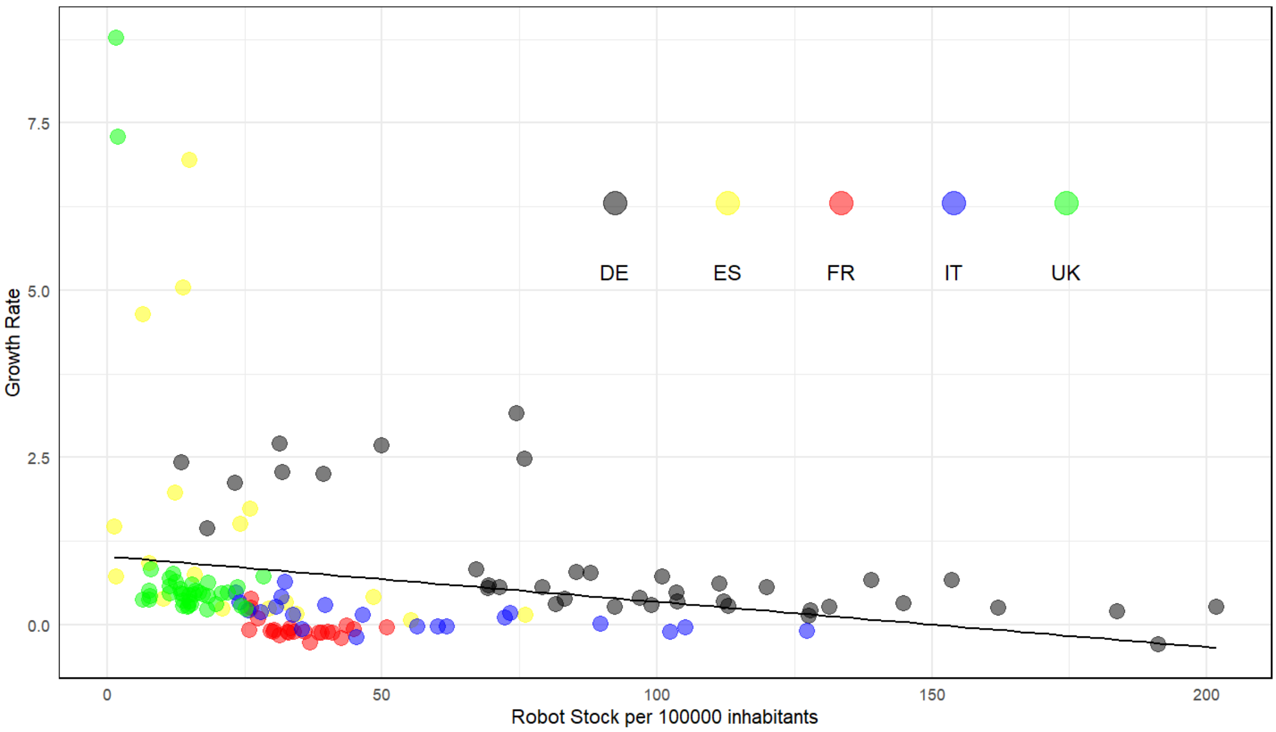
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Constant | -0.04 | 0.08 | -0.05 | 0.03 | 1.04 *** |
| | (0.1) | (0.1) | (0.12) | (0.12) | (0.17) |
| Pattern 1 vs 9 | 0.51 *** | 0.17 | 0.37 * | 0.24 | -0.09 |
| | (0.14) | (0.15) | (0.18) | (0.18) | (0.19) |
| Pattern 2 vs 9 | 0.68 *** | 0.35 | 0.70 ** | 0.73 ** | 0.50 * |
| | (0.19) | (0.19) | (0.25) | (0.26) | (0.19) |
| Pattern 3 vs 9 | 0.81 *** | 0.44 * | 0.69 ** | 0.54 * | 0.39 * |
| | (0.17) | (0.18) | (0.24) | (0.24) | (0.19) |
| Pattern 4 vs 9 | 0.60 *** | 0.25 | 0.41 * | 0.37 | -0.18 |
| | (0.15) | (0.16) | (0.18) | (0.2) | (0.18) |
| Pattern 5 vs 9 | 0.52 *** | 0.45 *** | 0.62 *** | 0.50 ** | -0.02 |
| | (0.14) | (0.13) | (0.15) | (0.15) | (0.17) |
| Pattern 6 vs 9 | 0.23 | 0.12 | 0.28 | 0.24 | 0.13 |
| | (0.13) | (0.13) | (0.15) | (0.15) | (0.11) |
| Pattern 7 vs 9 | 0.51 ** | 0.56 *** | 0.64 *** | 0.58 ** | 0.07 |
| | (0.17) | (0.16) | (0.17) | (0.2) | (0.18) |
| Pattern 8 vs 9 | 0.39 ** | 0.62 *** | 0.53 ** | 0.38 * | -0.05 |
| | (0.15) | (0.15) | (0.16) | (0.19) | (0.18) |
| Log_ROBOTpc_ | | -0.25 *** | -0.29 *** | -0.25 *** | -0.62 *** |
| | | (0.05) | (0.07) | (0.07) | (0.06) |
| UV | | | -0.08 | -0.09 | 0.07 |
| | | | (0.05) | (0.05) | (0.04) |
| RV | | | 0.11 | 0.1 | 0.36 *** |
| | | | (0.08) | (0.08) | (0.06) |
| HK | | | | 0.12 * | 0.15 ** |
| | | | | (0.05) | (0.05) |
| RDpc | | | | -0.08 | 0.04 |
| | | | | (0.05) | (0.04) |
| PATpc_ | | | | 0.04 | -0.04 |
| | | | | (0.07) | (0.05) |

| | | | | | |
|---|---|---|---|---|---|
| GDPpc | | | | -0.05 | -0.03 |
| | | | | (0.05) | (0.04) |
| SPAIN vs. GERMANY | | | | | -0.74 *** |
| | | | | | (0.17) |
| FRANCE vs. GERMANY | | | | | -1.31 *** |
| | | | | | (0.16) |
| ITALY vs. GERMANY | | | | | -0.64 *** |
| | | | | | (0.18) |
| UK vs. GERMANY | | | | | -1.08 *** |
| | | | | | (0.13) |
| Observations | 137 | 137 | 137 | 137 | 137 |
| R-squared | 0.23 | 0.34 | 0.36 | 0.41 | 0.7 |

Standard errors are heteroskedasticity robust. ***p <0.001; **p < 0.01; * p< 0

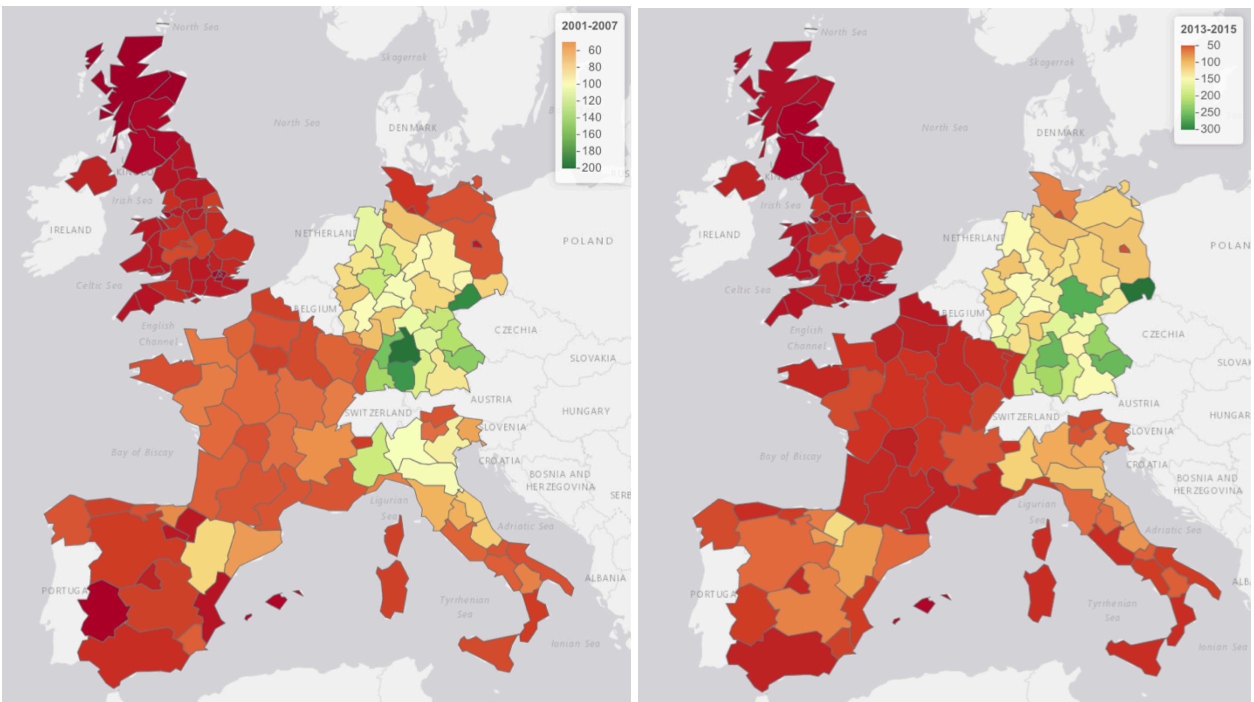
## Figures

**Figure 1.** Robot adoption in selected European regions: average stock (Period II) and average growth rate between Period I and II



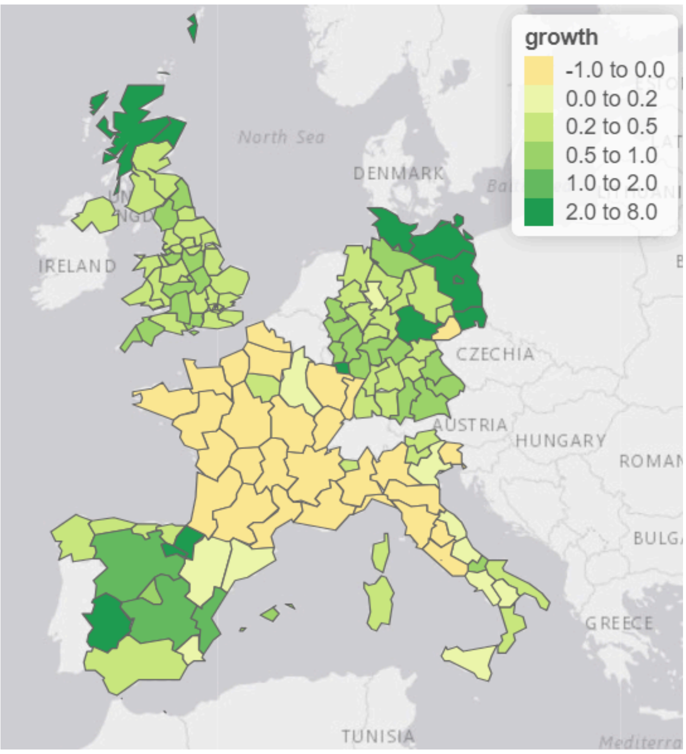

Source: author's estimates on IFR data (2017)

**Figure 2a and 2b.** Average robot stock in Period I and Period II in selected European Regions per 100k inhabitants



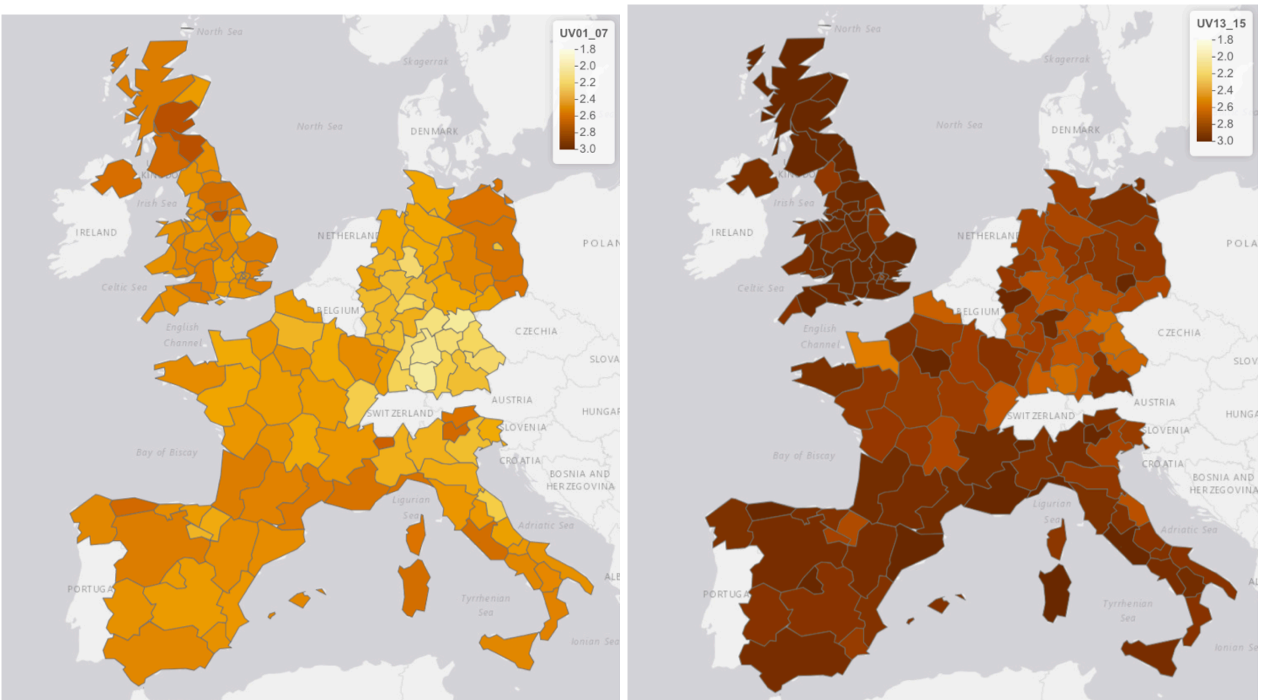
Source: author's estimates on IFR data (2017)

**Figure 3.** Robot Growth rate in selected European Regions (average growth per 100k inhabitants between Period I and II)



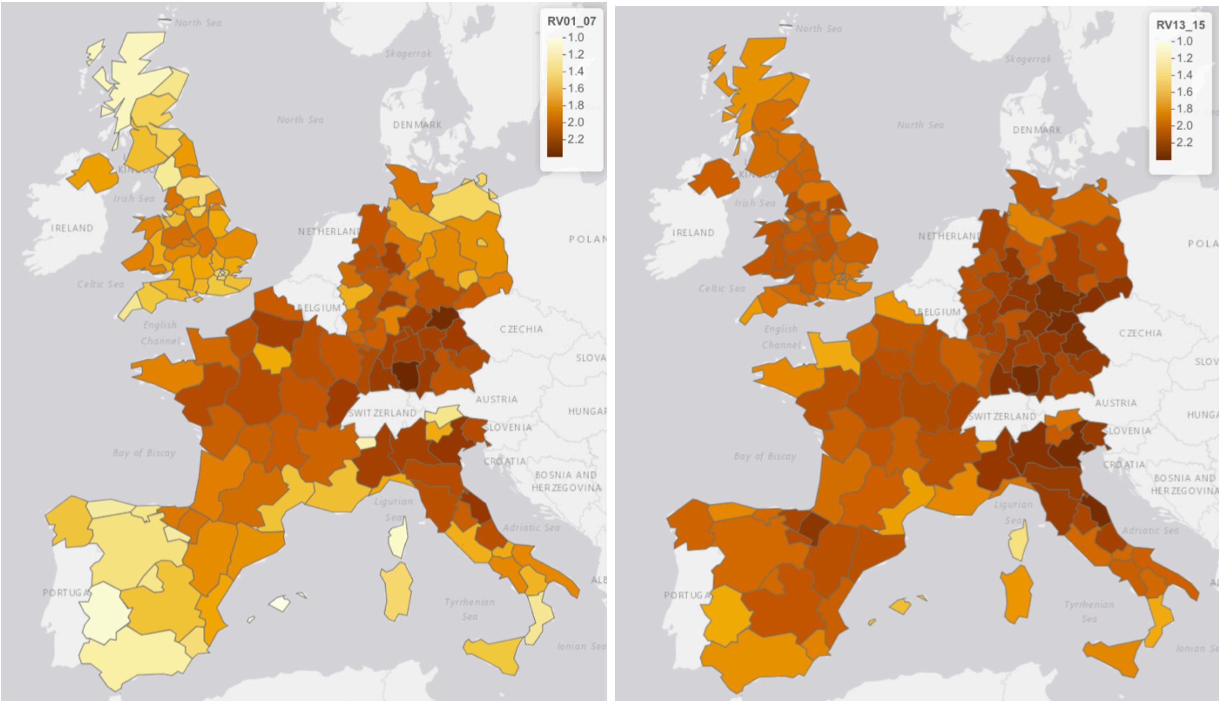

Source: author's estimates on IFR data (2017)

**Figure 4a and 4b.** Unrelated Variety in Period I (left) and II (right)



Source: Authors' estimates on EUROSTAT SBS

**Figure 5a and 5b.** Related Variety in Period I (left) and II (right)




Source: Authors' estimates on EUROSTAT SBS

**Figure 6.** Unified Distance Matrix in Period I and nine regional patterns

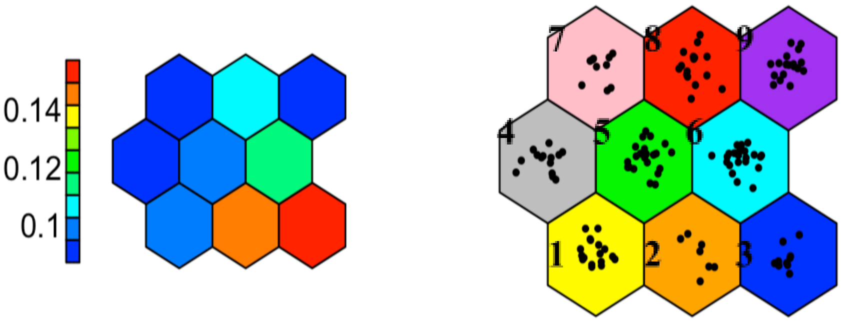


**Figure 7.** Regions and industrial patterns in Period I

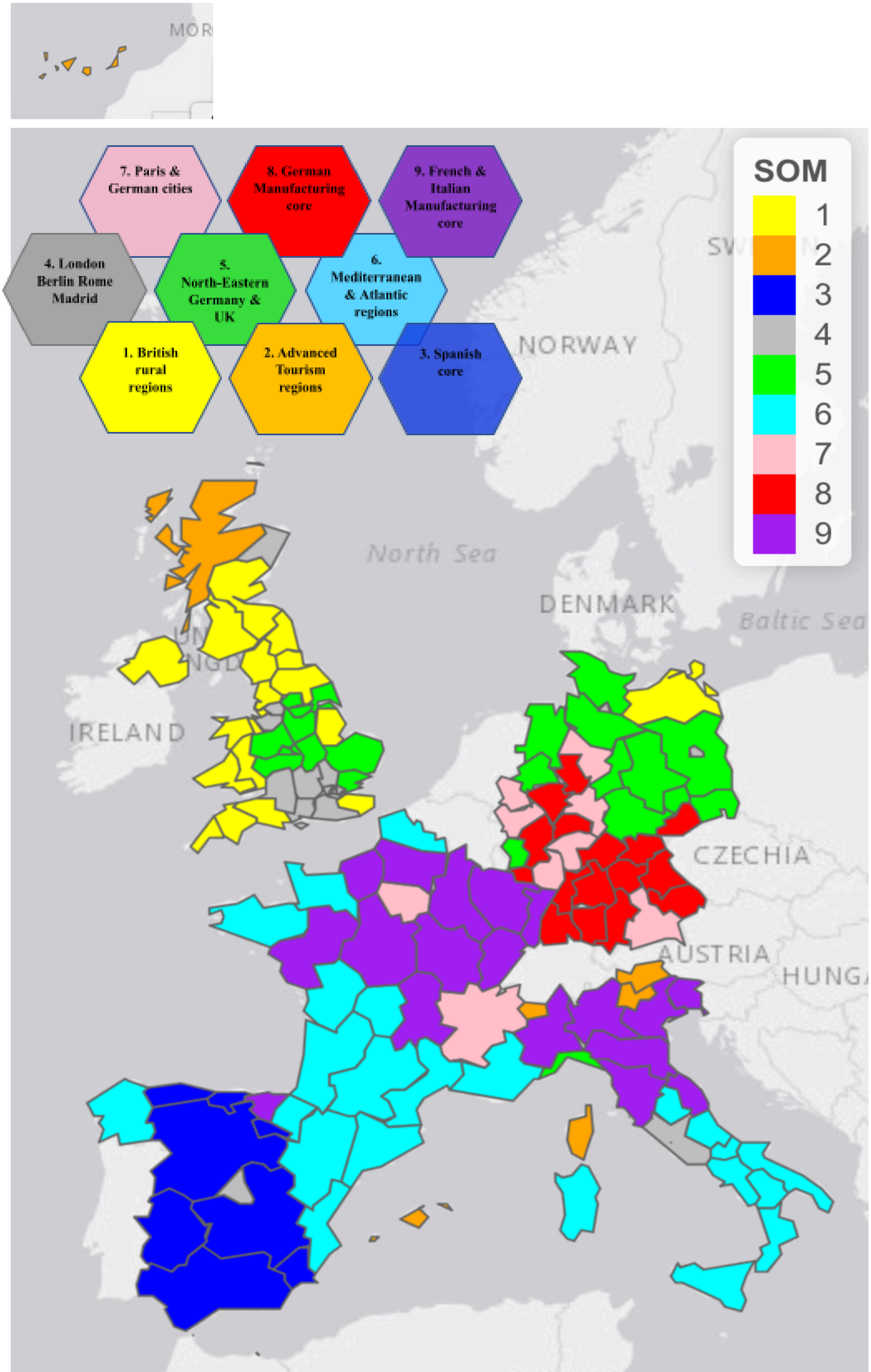


**Figure 8.** Robot growth rate in nine European regional patterns