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Industrial pattern and robot adoption in European regions

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Abstract. Recent literature on the diffusion of robots mostly ignores the regional dimension. The contribution of this paper at the debate on Industry 4.0 is twofold. First, IFR (2017) data on acquisitions of industrial robots in the five largest European economies are rescaled at regional levels to draw a first picture of winners and losers in the European race for advanced manufacturing. Second, using an unsupervised machine learning approach to classify regions based on their composition of industries. The paper provides novel evidence of the relationship between industry mix and the regional capability of adopting robots in the industrial processes.

Keywords: Robots, Industry 4.0., Innovation, Industry Mix, Self-Organizing Maps

JEL classification: E32, O33, R11, R12

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Introduction

Advanced manufacturing is likely to become a key competitive advantage for those cities and regions able to master the recombination of new digital technologies with traditional manufacturing capabilities shifting to a radically new system of production (Kagermann, 2015). Since buzzwords emerge faster than the innovation waves they describe, conceptualization of Industry 4.0 remains vague, although it can be considered the result of convergence of advances in several related information and communication technologies (ICTs), in computer science such as artificial intelligence (AI), cloud computing, the Internet of things (IoT) and industrial robotics. Beyond affecting the way things are produced and distributed, the so-called fourth industrial revolution will transform the dynamics of customer engagement, value creation, management and regulation (Schwab, 2017).

There is a growing debate on the impact of robotics on jobs (among the others, see Acemoglu and Restrepo, 2018; MIT Work of the Future, 2019). As largely documented from former industrial revolutions (Mokyr et al., 2015, Woirol, 1996), the expected effect on employment is not straightforward. First, the manufacturing sector has already been affected by a first long wave of automation since the 1980s which heavily reduced the workforce employed in the industry. Thus, further reduction in the workforce requires complementary organizational changes and, in the short run, it is likely to meet institutional resistance and managerial challenges. Secondly, since automation in advance manufacturing is heavily related with ICT, its deployment, use, and maintenance require new competencies. Third, advance in ICT allows new forms of interaction between humans and machines, which might transform machineries into a labour augmenting- rather than a labour substituting technology. Finally, and most important, if advanced automation became a key advantage in increasing both product quality and productivity of an economy a possible negative direct effect on employment might be more than compensated by the indirect positive effect generated by the increased competitiveness.

Differently from the above literature on technological unemployment, this paper looks at advanced automation as a key competitive advantage in the next future of industrial production. The emergence of new sectors and the adoption of new technologies do not appear in a vacuum, but they rest on the existing regional specialization. The aim of this paper is to identify the industrial antecedents of advanced manufacturing by associating the recent evolution in robot density at the regional level in the five biggest European countries (France, Germany, Italy, Spain and United Kingdom) with their corresponding industrial profiles before the 2008 financial crisis. In other words, we answer two main questions: What regions have accelerated in the race toward robot adoption? What profile of industrial specialization and/or diversification is paired

with this growth? We are interested in understanding which regional specific pattern of specialization can spur the change toward advance manufacturing and which, on the contrary, are on the verge of disruption.

We assume that rather than observing a direct impact of automation on employment (Arntz et al., 2016), we are experiencing a polarization between economies that grow because of the early adoption of automation (and associated organizational change) and economies that shrink because they were not able to catch up. These dynamics will happen more evidently at the regional level rather than at the country level. This idea is not simply inspired by the effect of digital transformation on manufacturing, but it is based on an empirical evidence of the growing polarization of both GDP and skills in Europe (Cirillo and Guarascio, 2015). Therefore, any consideration on the future of employment shall take a between- rather than within-region perspective and the pivotal research question concerns the ability of local economy to switch rapidly and adapt to the new mode of production.

We also assume that the switch of a local economy to the new mode of production depends very much on its labour competencies. A large stream of literature on related variety (Frenken et al., 2007) suggests that regional diversification has a positive impact on economic performances when new sectors maintain a large similarity in the input of production. The underlying idea is that diversification relies on existing competencies that are recombined into a new industry. Although our contribution is set among the research exploring the links between industry mix and innovation, we challenge the traditional definitions of related- and unrelated variety and we test a new operational definition of industrial relatedness being aware that “*relatedness is not about over-specialization*” but “*about understanding the unique paths that lead to diversification*” (Hidalgo et al., 2018, 454). We apply unsupervised learning neural networks, namely Self-Organising Maps or SOM (Kohonen, 1990), to cluster local economies along their profile of specialization and/or diversification. The SOM algorithm allows classifying regions on the basis of non-linear interactions of features, which, in our case, are the employment share in different industrial sectors. With this methodology we are able to capture complementarities among industries and their pattern evolution over time (Carlei and Nuccio, 2014).

Our framework has been inspired by 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 low-tech industries into advanced manufactured. This approach shows both theoretically and empirically that global trend to diversification into new industries is not random but follows specific paths. While the Atlas of Complexity maps knowledge recombination highlighting network connections between industries and countries,

the SOM approach stresses similarities projecting the vector distance between regions on a 2-dimensions topological grid.

First, we identify nine patterns built on the regional industry mix during the positive economic cycle between 2001 and 2007 (Period I). Second, we analyse their different propensity to adopt robots in the recovery phase 2013-2015 (Period II) that follows the downturn 2008-2012. Patterns can classify remarkably well different areas according to their adoption of industrial robot, while other traditional measures of both innovative activities (patent, R&D spending, percentage of high skilled workers) and economic performance (GDP, employment) are not necessarily consistent with industrial transformation of regions. We portray the emergence of Industry 4.0 proxied by the adoption of industrial robots as a complex phenomenon which points at the inner composition of the local economy rather than at the performance of synthetic indicators.

The paper is organised as follows. The next section presents how the notion of industry mix has been conceived and operationalized in the economic geography literature and how it can affect innovation processes. Section three presents the data and describes the adoption of robots in European regions. Section four applies our approach to cluster similar regions into patterns of macro-regions based on industrial mix and section five tests the relationship between this classification and the diffusion of robots. In conclusion we discuss implication for regional development and innovation policies.

1. Regional industry mix and its relationship with innovation

The industry profile of a region is the idiosyncratic result of a process of economic development which evolved overtime together with competences and skills of workers, socio-demographics characteristics, and institutions. In some cases, regional systems can facilitate the adoption of new technology or almost spontaneously branch new sectors, while in others which are locked-in the present economic activities, obstacles prevail and impede the structural change of the economy.

The academic debate around the role of regional industry mix in explaining both innovative performance and economic growth has followed two complementary approaches. In the first approach, regional economic structure has been analysed in terms of distinctiveness of its industrial composition. Probably the most popular technique adopted to describe the dynamics of industry mix from a comparative perspective is the shift and share analysis, which decomposes differences between values of a chosen variable as observed at the regional and national level (Buck, 1970). Although its many limitations, this technique has been largely 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 second approach is even older and draws on two recurrent and often overlapping topics in economics: spatial concentration and industrial specialization. Although different in nature, concentration and specialization are considered at the origin of positive externalities and, therefore, have always been studied as source of localized advantages since Smith (1776) and Marshall (1890). In both classical authors, we can find the idea that agglomeration and specialization go together since i) they rise productivity by sharing suppliers and labour market and ii) they generate knowledge spillovers speeding up innovation and growth. Unlike the economic literature, Jacobs (1961) suggested that density and diversity of human activities are the engine of the rapid growth of cities. According to Jacobs (1961: 145), cities are “*natural generators of diversity and prolific incubators of new enterprises*” because they are dense and, therefore, offer “small manufacturers” a wider variety in commerce, services and entertainment. Beginning with Glaeser et al. (1992) and Duranton and Puga (2001), a large body of empirical research tried to compare the effect of MAR vs Jacobs externalities with inconclusive results (de Groot, Poot, & Smit, 2016). The seminal contribution by Frenken et al. (2007) on related variety (RV) and unrelated variety (UV) can be considered an extension and a specification of the work on urban agglomeration by Jacobs (1961). In order for advantages of diversity to fully display, Frenken et al. (2007) argue that not only spatial concentration matters, but also knowledge produced and exchanged at the local level has to be related somehow.

Although Content and Frenken (2016) argue that the RV thesis holds, they also warn of inconsistency in the use of dependent variables that include employment growth, productivity growth and GDP growth and suggest exploring new relationships between the advantages of diversification and respectively, innovation, knowledge and entrepreneurship. Among the latest papers testing the effect of RV and UV, we can recognise two main research areas which our paper contributes to. A first stream of literature investigates the effect of RV on innovation, typically measured in terms of patents. For example, Boschma and Capone (2015) and Castaldi et al. (2015) find that it is not clear which relatedness has stronger effect on innovation although they suggest RV favouring incremental innovation and UV being a more fertile environment for radical innovation.

A second promising approach has concentrated on the effect on regional and industrial resilience. According to Cortinovis & van Oort (2015) RV is limited within specific sectors and, therefore, regions with a higher UV are more resilient to shock 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. Although in this paper we do not draw inference between the two aspects, we are able to describe those pre-crisis patterns of economic activities where robotics has found a fertile background to expand.

From an empirical perspective, Content and Frenken (2016) also wonder what the best method to capture RV is and what other dimensions could contribute to grasp relatedness. Usually, industrial proximity among the underlying structure of “shared or complementary competences” (Boshma and Iammarino, 2009) has been measured in terms of input similarity, co-occurrences of trade activities or skill-relatedness. Instead, we focus on the employment composition of the economy as a proxy for human capital, assuming that the number of employees in one sector implicitly accounts for set of competences and capabilities. In particular, we apply a pattern recognition technique (Carlei and Nuccio, 2014) to find spatial similarities based on the regional distribution of the industrial employment. This approach is built on Self-Organizing Maps or SOM (Kohonen, 1990), which are among the most important and widely used neural network architectures and allow to reveal spatial similarity by exploiting regional variation in the distribution of local employment over different industries.

The output of the SOM is not a single measure, such as for relatedness concepts, but a map which classifies regions and provides the underlying profile of specialization which characterizes each cluster. In this way, this approach is much more similar to the complexity approach by Hidalgo et al. (2018), which reveals a structure, while the RV and UV concept only summarize it.

This approach does not only overcome some of the limitations of the variety measures, but it seems more consistent with a policy perspective because SOM measures relatedness indirectly through the regional similarity and derive industrial mix *ex-post* from data. 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). We are able to show that the diffusion of Industry 4.0, as proxied by the adoption of industrial robots, started with but it is not limited to regions specialised in advanced manufacturing. To this respect we argue that the RV/UV approach cannot reveal the structural features which led regions on different adoption path.

2. The regional map of industrial robots in major European countries

Although industrial robots have been employed for decades in European manufacturing activity, they are at the moment tightly interlinked with the spread of Industry 4.0 (Bahrin et al., 2016, Lee et al., 2014). The production and use of highly autonomous robots require de facto the development of complementary solutions in sensors, cloud storing, analytics and computing power.

Estolatan et al. (2018) show that the robotics landscape in Europe remains uneven. On the one hand, Germany and Italy (together with Japan and US) lead the world-wide market for industrial automation, on the other France and UK have been facing opposition stemming from the potential displacement of labour force (William, 2016). As a reference, outside Europe the most important hubs for industrial robotics are Japan, industry leader, and the U.S., where there are no companies among the market leaders in the production and most firms are robot system integrator (IFR, 2017).

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 firms¹ 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 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 region 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”. 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**).

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.

We focus on 137 NUTS 2 regions (Eurostat, 2011) of five European countries,⁴ i.e. France, Germany, Italy, Spain and 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 the 1993 as the initial value of the stock in our PIM (Graetz and Michaels, 2018). The 15 annual country aggregated stocks of robots (i.e. one for each of the 15 considered industries) are allocated to the 137 regions using the number of firms per industry as in the following equation:

$$Robot\ stock_{i,t} = \sum_{j=1}^{15} \frac{No\ Firm_{j,i,t}}{National\ No\ Firm_{j,i,t}} * National\ Robot\ stock_{j,i,t} \quad [1]$$

where $Robot\ stock_{i,t}$ is the stock of robots in region i at year t ; $No\ Firm_{j,i,t}$ and $National\ No\ Firm_{j,i,t}$ are, respectively, the regional and national number of firms in industry j in region i at year t ; and $National\ Robot\ stock_{j,i,t}$ is the national stock of robots in industry j in region i at year t .⁵ 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).⁶

In 2015 the five countries considered in this report account 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 (**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. Stock of robots adoption in the five major European countries

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.

⁵ Our measure of robot stock might be affected by cross-regional differences in firm characteristics such as firm size and firm technologies. To account for these differences, we compute an additional measure of robot stock using data on regional value added. The availability of data (from national statistical offices) on regional industry value added, especially for manufacturing industries, limit our analysis to Italy and UK. So, the annual industry stock of robots at country level for these two countries are attributed to regions according to regional value-added shares instead of the regional firm shares. The correlation between the regional robot stocks computed using the two types of data 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.

⁶ Data on annual regional population are provided by EUROSTAT.

	2001		2007		2015		Growth rate 2001-2015
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%	
EU-EUROPE	232603		328890		433303		46%

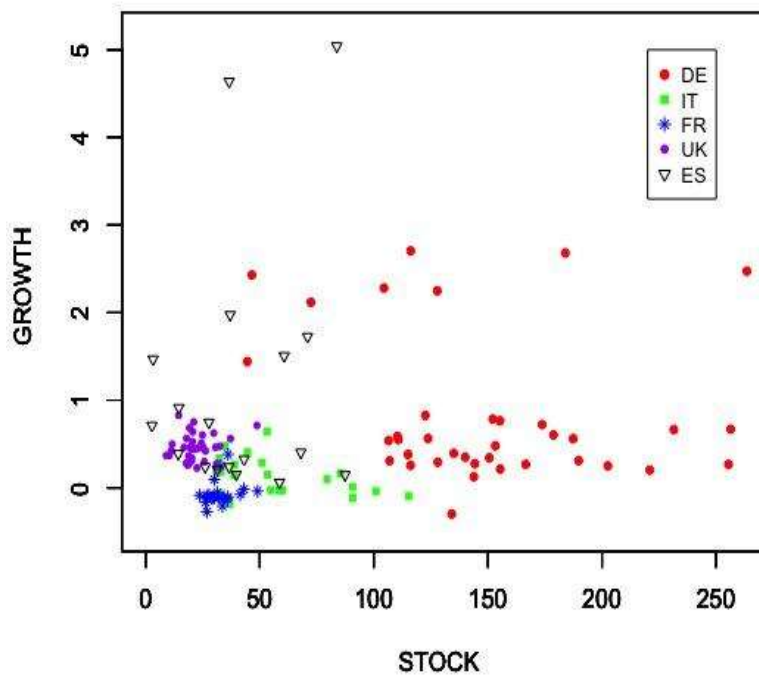
Table 2. Stock of robots adoption in the top European regions

Region				Average Stock 2013-2015
1	DE	DE11	Stuttgart	10160.64
2	IT	ITC4	Lombardia	9003.558
3	DE	DE21	Oberbayern	6800.09
4	DE	DEA1	Düsseldorf	6303.31
5	DE	DEG0	Thüringen	5698.031
6	DE	DEA5	Arnsberg	5526.81
7	DE	DE12	Karlsruhe	5477.54
8	IT	ITC1	Piemonte	5084.788
9	DE	DED2	Dresden	4922.9
10	DE	DEA2	Köln	4786.401
11	IT	ITH5	Emilia-Romagna	4466.516
12	IT	ITH3	Veneto	4455.11
13	ES	ES51	Cataluña	4360.845
14	FR	FR10	Île de France	4341.187
15	DE	DE71	Darmstadt	4237.546
16	DE	DE13	Freiburg	4130.455
17	DE	DE14	Tübingen	3940.298
18	DE	DE94	Weser-Ems	3690.593
19	DE	DE27	Schwaben	3386.578
20	FR	FR71	Rhône-Alpes	3168.091
Tot 20 regions				49%
Tot 137 regions				100%

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 robots for all 137 regions considered (**Figure 1**) confirms the negative relation between stock and growth and strong country effect. British regions are very concentrated in 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.

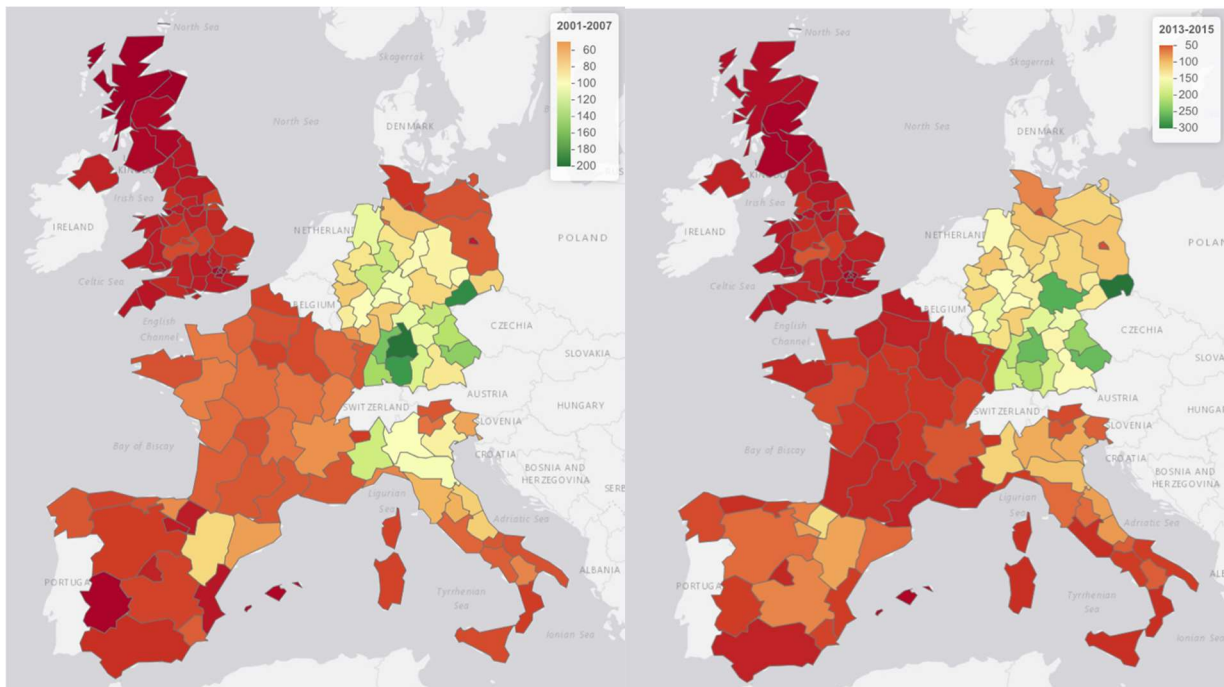
Germany has got the highest within-country heterogeneity. Some German regions like Dresden and Thüringen combine a good level of robot penetration with a sustained growth. Other regions like Stuttgart and Chemnitz are endowed with a very high stock but have not grown between the two periods. City-states like Berlin and Hamburg started from a very low stock and shows a moderate-high growth rate of robots. The within- and between country heterogeneity is more clearly visible in **Figures 2** and **Figures 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 are still heavily affected by national policies, which apply to both more- and less economically advanced regions. Robot stock is quite remarkable in the whole 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*. Despite some converging trends there is a strong regional variation to be addressed. In the remainder of the paper we link industry profile of regions with their performance in the adoption of robots.

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



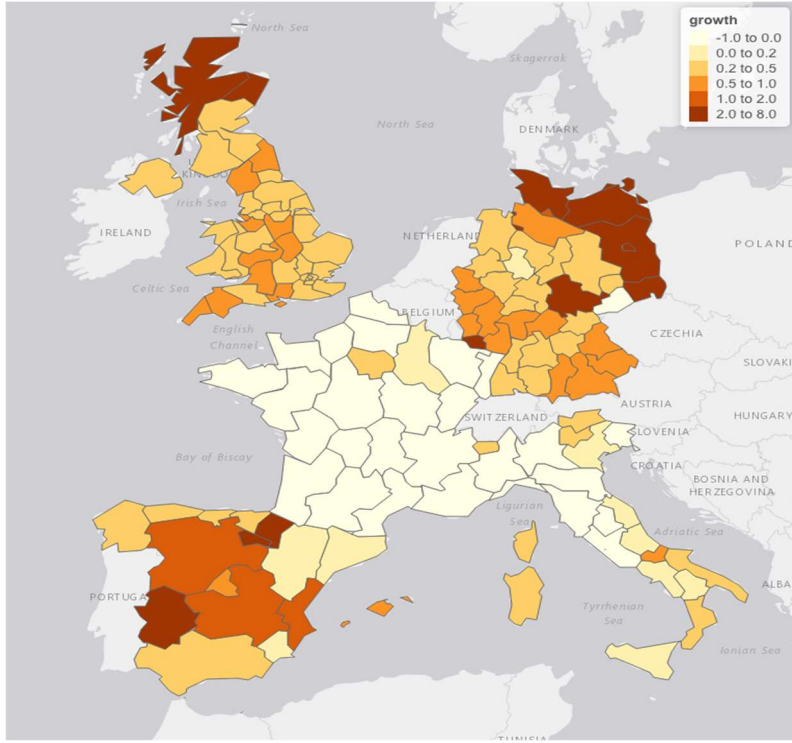
Source: author's estimates on IFR data (2017)

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)

3. Comparative approaches to the analysis of industry mix

The paper compares two different approaches to measure industrial mix at the regional level: 1) RV and UV indicators are used to define similarity (diversity) across industries in the same region, while 2) pattern recognition based on SOM depicts similarity across regions considering all their industries. Following Caragliu et al., 2016 we use the available employment data to calculate RV and UV:

$$UV_r = \sum_{g=1}^G P_g \log_2 \frac{1}{P_g} \quad [2]$$

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

$$RV_r = \sum_{g=1}^G P_g H_g, \text{ where } H_g = \sum \frac{P_i}{P_g} \log_2 \frac{1}{P_i/P_g} \quad [3]$$

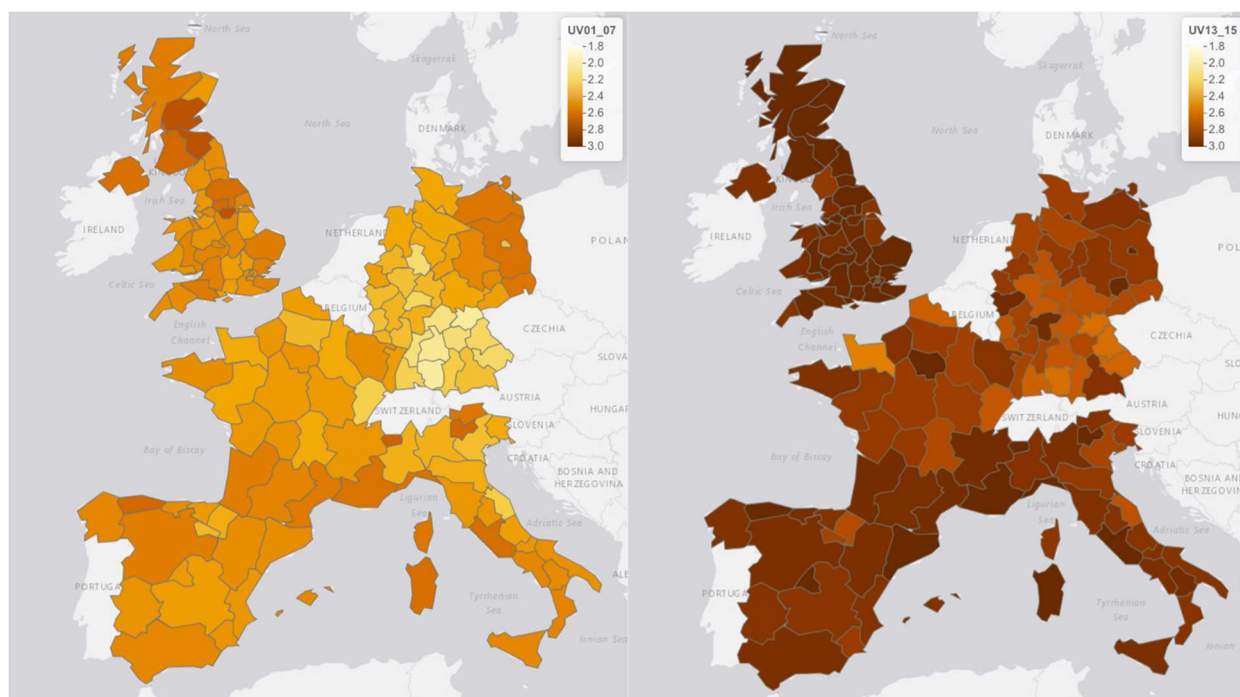
with P_i = share of employment in the 2-digit sector i .

RV is the weighted sum of the entropy indicator at the two-digit level within each one-digit class, while UV is the entropy of one-digit distribution. Our measure of RV assumes that two industries are more related to each other when both industries share the same one-digit class. For example, the “Manufacture of machinery and equipment industry” (NACE 2011: C28) is more

related to the “Manufacture of electrical equipment industry” (NACE 2011: C27) than to “Construction of buildings” industry (NACE 2011: F41). By contrast, UV measures the extent to which a region is diversified in different one-digit industries. From a dynamic point view, changes in the RV and UV are determined by variations in the total number of industries and/or in the relative weight of each industry.

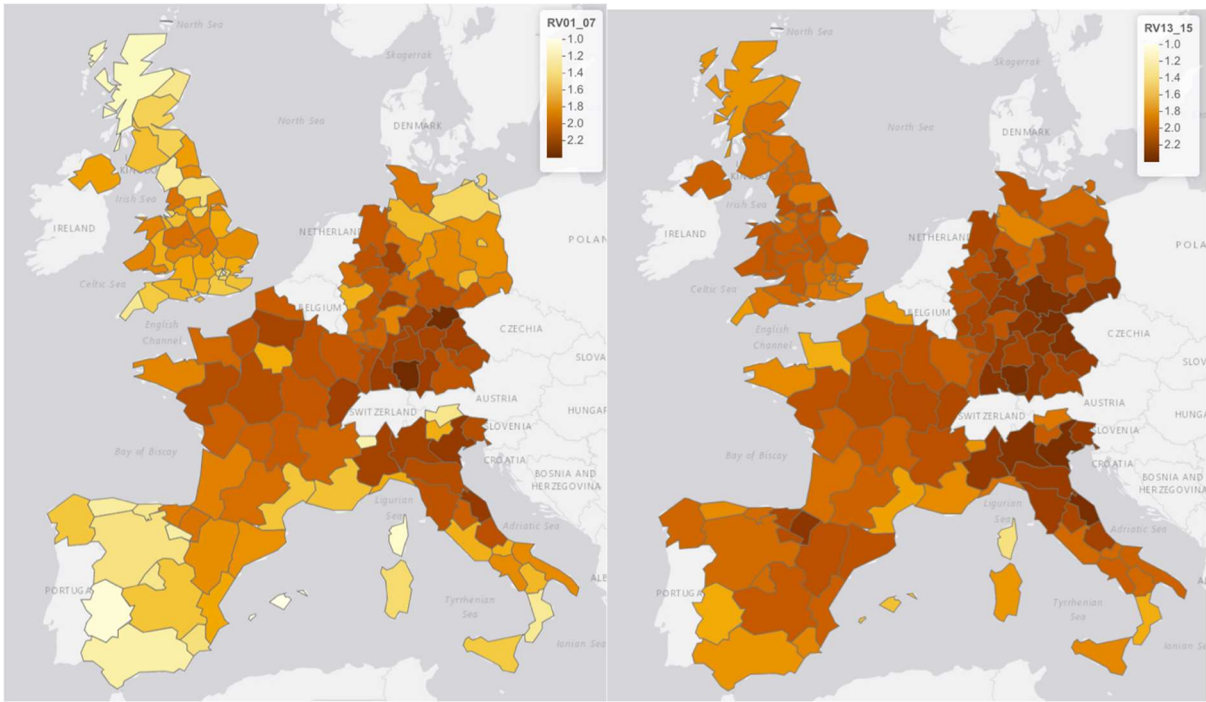
Comparing these two measures respectively in the Period I and II we observe that the UV has grown substantially and has particularly concentrated in a few regions (**Figure 4a and 4b**). While in Period I was quite uniformly distributed over European regions, in Period II we observe very high values in the UK and in the major metropolitan areas including all capital cities, but also in some Mediterranean regions of Italy, France and Spain. Although also RV has increased over time, the map of regions seems more stable and shows a lower variance of values (**Figure 5a and 5b**). The upper range values are particularly concentrated in around the Alps, namely in Southern Germany, Northern and Central Italy, and to a lesser extend in a few regions in Eastern Spain, Northern France and Central England.

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

It is relevant to mention that UV and RV show a moderate, but significant negative correlation (**Table 3**), which is not explained by a robust theoretical hypothesis. Depending strongly on pre-given industrial classification tiers, RV is positively correlated with most of manufacturing sectors (section D in the NACE classification) while UV is mainly growing when advanced services grow. What can RV and UV respectively suggest about robot adoption? Not surprisingly, both measures are correlated to robot stock, although it is totally obscure the relationship with robot growth rate. Following the above bias, these indicators simply confirm that more manufacturing in a region attracts more robots, but nothing can be understood about the industry mix and the differences in robots between regions with same RV or UV.

Table 3. Correlation table: RV, UV and Robots

	RV13_15	UV13_15	RV01_02	UV01_02	rob stock Period II
RV13_15					
UV13_15	-0.38****				
RV01_02	0.84****	-0.45****			
UV01_02	-0.37****	0.72****	-0.42****		
rob stock Period II	0.66****	-0.62****	0.55****	-0.55****	
rob growth Period I-II	-0.08	0.03	-0.28***	-0.01	0.1

$p < .0001$, ****, $< .001$, ***, $< .01$, **, $< .05$, *

In the light of this unpromising approach, we offer a second method to detect differences in industrial mix. The following analysis based on SOM 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, it is more effective than a mere regional classification to suggest which different industry profiles explain a different value of RV and UV and, therefore, allows for a sector specific analysis of patterns.

The SOM represents a nonlinear transformation from a continuous input space to a spatially discrete output space: the feature map preserves the topological relationship that exists in the input space, but with a lower dimensionality. These dimensionality reduction techniques are also used to reduce two undesired characteristics in data namely noise (variance) and redundancy (highly correlated variables). The key element of a SOM network is the Kohonen Layer (KL), which is made up of spatially ordered neurons named Processing Elements (PEs), and evolves through a competitive learning process up to assign a representative industry pattern to each PE. The PE whose weight vector is most similar to the input is called the best matching unit (BMU). The weights W_v of the BMU and neurons close to it in the SOM grid (neighbourhood) are adjusted at the iteration s according to the following formula:

$$W_v(s + 1) = W_v(s) + \vartheta(u, v, s) \alpha(s) (D(t) - W_v(s)), \quad [4]$$

where ϑ is neighbourhood function, α is learning restraint due to iteration and $D(t)$ is the target input data vector.

The dataset to train the SOM algorithm is obtained from 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 $i = 1 \dots n$ of the 137 European regions (NUTS 2) per $j = 1 \dots m$ industries (2-digits). Although it would be possible to show the temporal evolution of the industry mix before and after the 2008 financial crisis, for the specific purpose of this paper we only run SOM in the Period I.

According to equation [4], we trained a feature map (or SOM grid) composed of 9 different patterns (3*3 PEs)⁷ which have clustered all the 137 European regions (**Figures 6**). When plotting these patterns on a geographical map (**Figures 7**) we are not surprised to find a geographical contiguity of regions within the same pattern. Before any specific consideration on the nature of the patterns, this result highlights the effectiveness of the SOM approach to track

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.

the uneven, yet not random diffusion of industrial specialization since topological proximity on SOM grid 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 industry⁸.

Figure 6. Patterns of regions and Unified Distance Matrix in Period I

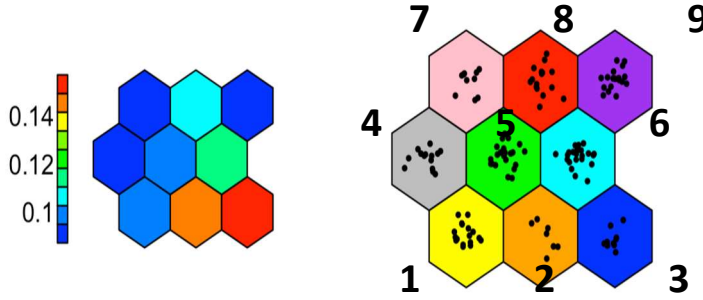
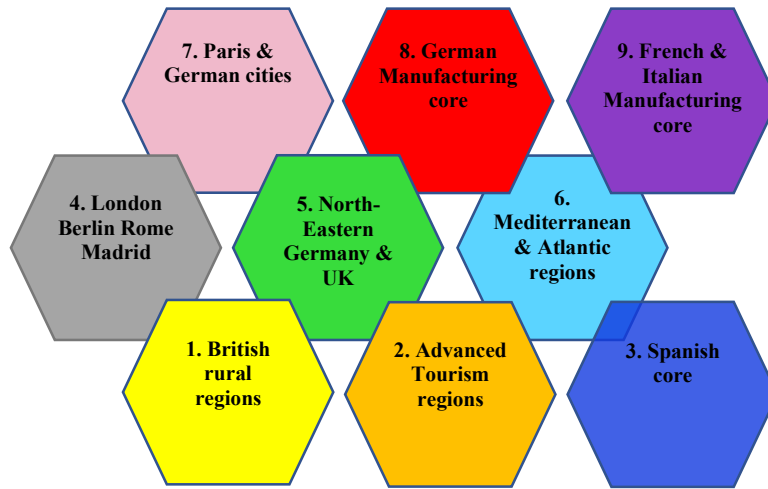
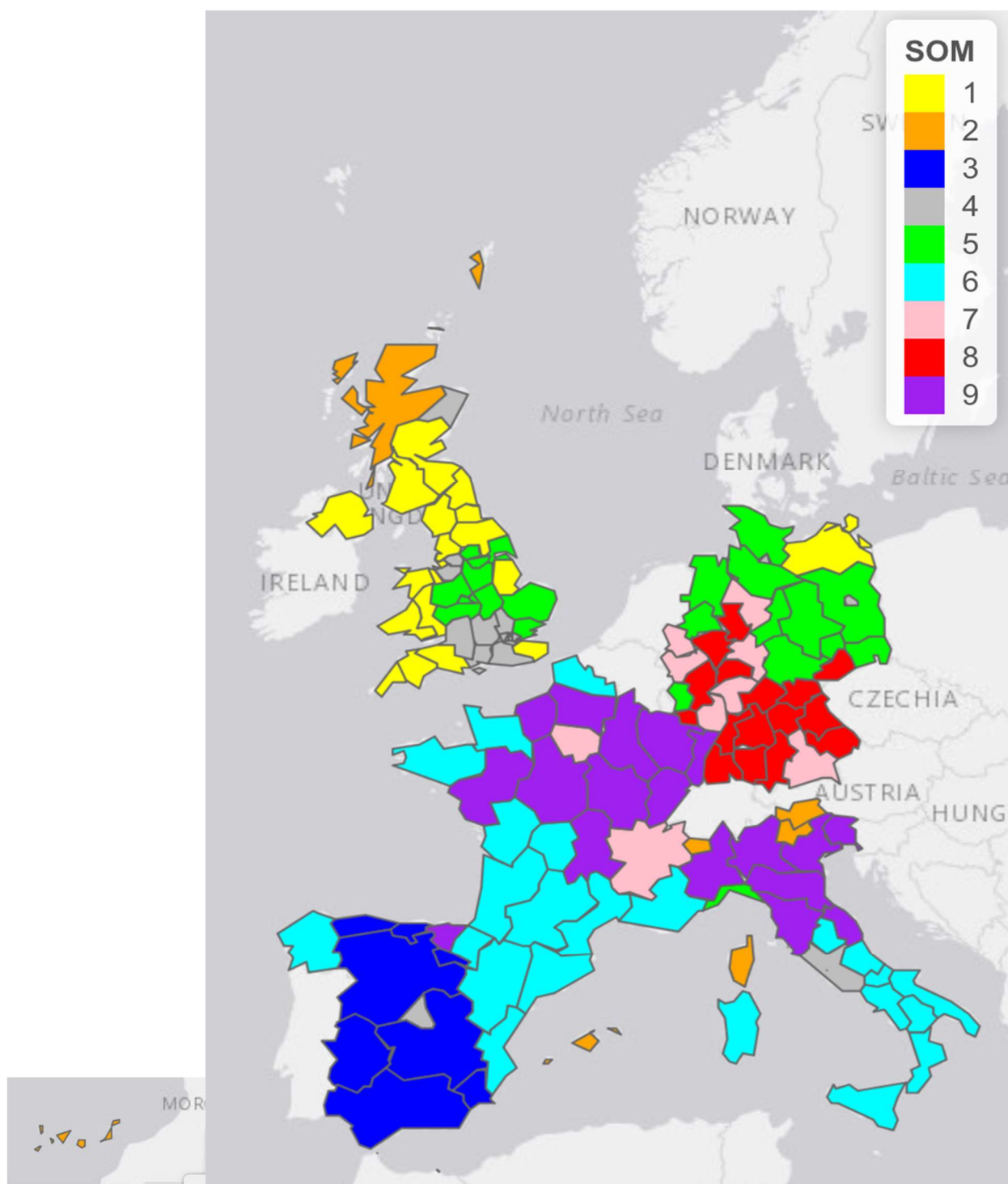


Figure 7. Regions and industrial patterns in Period I



⁸ For each industry j the SOM releases a codebook, i.e. the convergence value between 0 and 1 of the weight W_j , 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)



In the following paragraphs we present a taxonomy of European regions and some key traits of each pattern identified in Period I (**Table 4**). Beginning from the top-right of the feature map (**Figure 6**) we find macro-regional patterns based on different manufacturing mix (7, and 8). Predominately 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.

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 SOM grid 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.

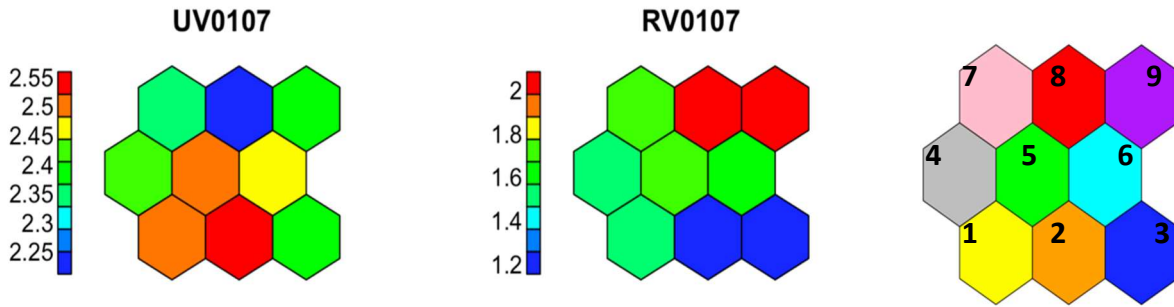
Both patterns in the bottom-left of the feature map (1 and 2) are tourism-based economies, but only the latter is specialised and covers the most popular European destinations from the Canarias Islands to Alps, while the latter include regions in marginal tourism areas, mostly in the rural UK. Eventually, in the middle of the SOM grid 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.

To compare the results obtained from the two methods of measurement of industrial mix and assess their relative strengths, we plot UV and RV on the SOM map (**Figure 8**). UV is high in regions specialized in sectors based on local resources such as tourism (pattern 1 and 2). This does not come with a surprise since the random distribution of natural resources is independent by the specialization in other sectors. It is less obvious that UV does not characterize large cities and capitals (pattern 7 and 4), in which, based on Jacob's externalities, should exhibit a large unrelatedness. On the contrary, RV is particularly high in the right-upper side of the feature map, namely the two manufacturing-oriented patterns in Germany, Italy and France (8 and 9).

Table 4. A taxonomy of European Regions 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

Figure 8. Distribution of Unrelated and Related Variety on the SOM map (Period I)



From a methodological perspective, the distribution of UV and RV over the SOM map suggests that although these indicators tend to mirror different geographies, they are not totally specular and can even overlap. In fact, both RV and UV can be very high (or very low) in relatively different combinations of industrial mix: not all cities have a strong UV and not all manufacturing regions have a strong RV; in other words, the synthetic nature of these indexes may harm the analysis. We have for instance a very low UV in pattern 7 (urban), pattern 9 (manufacturing) and pattern 3 (construction). On this basis, nothing can be said about the role of UR or RV as antecedent of industrial development, as in this case, robot adoption. Therefore, in order to overcome the limits of the overly synthetic nature of UR and RV, we show how the SOM classification can be interpreted to reveal the organization of industries at the regional level. Finally, we adopt the SOM classification to explore the industrial antecedents of robot adoption.

4. The diffusion of Industrial Robots in European macro-regions: absorptive capacity and economic performance

After classifying European regions in patterns of macro-regions and exploring their difference in term of variety of their industrial composition, we can eventually evaluate the extent to which the industry mix captured by the SOM is an antecedent to the penetration of industrial robots. Robot stock and robot growth is therefore associated respectively with measures of innovation capacity and indicators of economic performance over time.

The capacity of regions to adopt robots might be affected by their knowledge and technological characteristics. The existing literature argue that human capital (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. To measure the regions' absorptive capacity to adopt robots, we use three variables: the shares of

high skilled people, i.e. the shares of population aged 25-64 with a tertiary education⁹ (*High skilled share*); the R&D per capita expenditures (Euros per thousand inhabitants) (*R&D per capita*); the number of EPO patents per capita¹⁰ (patents per thousand inhabitants) (*Patent per capita*).¹¹

Table 5 compares the yearly average values in the period I of these three variables with yearly average values of robot stocks (*Robot stock*) in the period II across the different SOM patterns. It emerges that the endowment of a high skilled capital is not crucial in explaining the robot stock of regions. Indeed, regions with the higher shares of high skilled workers in period I, i.e. patterns 1 and 4, are also the regions with the lower stock of robots in period II (*Robot stock*). Moreover, although pattern 8 (German core) holds the highest stock of robots, it is also among those with the lower share of high skilled workers.¹² As a further confirmation, we observe a non-statistically significant correlation ($r = -0.08$, $p\text{-value} < 0.38$) between regional stock of robots and regional average share of high skilled workers. A similar picture emerges looking at the data on R&D per capita, i.e. patterns with the higher (lower) robot stocks are not necessarily those with the higher (lower) levels of R&D per capita and vice-versa (see, again, patterns 1 and 4 versus pattern 8),¹³ and the correlation between the two variables is non-statistically significant. However, we observe a strong positive and significant correlation between robots and patents per capita ($r = 0.60$, $p\text{-value} < 0.00$), possibly explained by a higher concentration of patents in German regions.¹⁴ These descriptive statistics highlight a non-linear relationship between the knowledge or technological level and the robot stock of regions and, more in general, support the mismatch between R&D capabilities and regional industrial structure (David et al., 2009). This non-linearity may be caused by several factors, which may vary between regions. Robot adoption may be, for example, affected by the local strength of labour unions, by government policies (Baldwin and Lin, 2002) and by local managerial resources (Graetz and Michaels, 2018).

⁹ 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).

¹⁰ Patents are assigned to regions using the inventors' addresses (see e.g.: Cappelli and Montobbio, 2016).

¹¹ To construct these variables, we use EUROSTAT REGIO data, with the exception of patent data for which we rely on ICRIS-PATSTAT database on EPO patent applications (Coffano and Tarasconi, 2014).

¹² To give an example, some UK regions in pattern 4 like Berkshire, Buckinghamshire and Oxfordshire (UKJ1) and Inner London (UKI1) show a high share of high-skilled (last quantile of the distribution) and a low stock of robots (last quintile) and, on the opposite, some German regions in pattern 8 like Oberpfalz (DE23) and Saarland (DEC0) show a low of high-skilled (first quintile) and a high share of stock of robots (last quintile).

¹³ Regions with a low level of R&D per capita are mainly located in South Italy and South-West Spain, while regions with a high level of R&D per capita are mainly located in North Italy, South Germany, South France and South UK.

¹⁴ If we exclude the German regions from the sample, the correlation drastically decreases and becomes not-significant ($r = 0.06$; $p\text{-value} = 0.58$).

We also consider the relationships between economic performance and robot adoption. The economic performance of regions are measured by the following three variables: growth rates (in percentage) between the yearly average values in the period I and the yearly average values in the period II¹⁵; the GDP per capita growth (Euros per thousand inhabitants) the employment rate of the age group 15-64 (*Employment*); the unemployment rate (of the age group 15-74, as percentage) (*Unemployment rate*). **Table 5** compares the growth rates of these three variables with the growth rates of robot stock (*Robot stock growth*) across the different SOM patterns. Again, we do not observe a univocal relation between robot stock growth and GDP per capita growth¹⁶ (see for example, pattern 3 vs pattern 8) and the same picture emerges from the data on employment and unemployment rate growth. Interestingly, the pattern with the lowest robot stock growth (pattern 9) does not show the lowest employment rate growth and/or the highest unemployment rate growth, confirming that, at least at the descriptive level, there is not a clear negative relationship between robot adoption and employment. On the contrary, if we compare robot diffusion in the highly successful manufacturing core respectively in Italy and Germany, we can appreciate that while Southern Germany (pattern 8) associates a positive growth in robots with a good performance in the labour market, Northern Italy (pattern 9) exhibits both a poor performance of the labour market and a decline in the diffusion of industrial robots. In general, regional robot stock growth rates are non-significantly correlated with regional employment growth rates ($r = 0.04$, $p\text{-value} = 0.65$) and with regional unemployment growth rates ($r = 0.05$, $p\text{-value} = 0.57$).

¹⁵ These variables are constructed using EUROSTAT REGIO data.

¹⁶ The correlation between regional robot stock and regional GDP per capita is 0.24 ($p\text{-value} = 0.00$).

Table 5. Knowledge and innovation indicators, economic performance indicators and robot adoption - mean values by SOM patterns

SOM (Period I)	Antecedents of Robots Adoption				Effects of Robots Adoption			
	High-skilled share (Period I)	R&D per capita (Period I)	Patent per capita (Period I)	Robot stock (Period II)	GDP per capita growth % (Period I – II)	Employment growth% (Period I – II)	Unemployment growth % (Period I-II)	Robot growth % (Period I-II)
1	27.36	0.23	0.06	14.33	1.87	2.15	22.59	64.58
2	17.20	0.12	0.04	20.10	-1.11	-0.50	98.10	164.26
3	23.80	0.10	0.01	18.45	-2.36	-8.46	137.00	159.35
4	32.70	0.66	0.15	14.78	3.19	1.81	21.99	110.91
5	24.52	0.31	0.11	49.89	7.43	7.27	-6.12	76.61
6	18.97	0.23	0.05	36.71	-2.90	-2.79	59.50	45.01
7	24.96	0.58	0.31	67.59	7.32	8.26	-28.93	66.37
8	21.83	0.35	0.34	135.14	13.30	9.97	-46.13	50.00
9	17.74	0.30	0.11	57.61	-3.75	-1.46	65.84	-3.47

The analysis based on pattern recognition allows to prompt some relevant implication also for innovation policies. First, from an industrial perspective, although the distribution of robots initially rewarded the strictly manufacturing regions, a convergence process has affected many regions with heterogenous industrial mix including business services, tourism and construction. Second, from a geographical perspective, the process of progressive adoption of advance manufacturing, on the one hand, follows macro-regional logics, on the other, still seems to be influenced by national fixed effects. Both of these aspects impose reconsider the scale of regional innovation systems and to implement smart specialization policies that do not focus only on leading knowledge regions, but also include diversified urban centres and intermediate and smaller urban-rural regions (Mcxann and Ortega-Argiles, 2015).

5. Conclusion

Building on the Industry 4.0 paradigm, this paper describes the regional diffusion of industrial robots in the five largest European economies and explores the industrial antecedents of advanced manufacturing associated with robot adoption. Not surprisingly, the regional map of robots penetration in Europe shows a stunning concentration of stock in the core manufacturing regions of Germany and Italy, while positive growth rates reward only Germany and some more peripheral European regions, thou excluding the traditional manufacturing clusters in Italy, France and UK.

Although there is a consensus on the intrinsic relationship between regional industrial mix and economic performances, economists and policy makers debate on the degree of industrial relatedness that can generate higher growth rates. Even less explored is the relationship between industry mix and innovation for example in the form of propensity to shift towards industry 4.0.

We test a new measure of industrial relatedness based on unsupervised neural networks (SOM) and we compare it with the widely adopted measure of related and unrelated variety proposed by Frenken et al. (2007). While the traditional approach behind industrial relatedness is based on the concentration of employment over a top-down classification of industries, the underlying principle of SOM algorithm is similarity across employment vectors of each region. In fact, SOM patterns are not biased by a pre-given hierarchical classification (e.g. NACE) since each region in the input is defined by its overall distribution of employment irrespective of the digits considered. We claim that our approach allows a full exploration of regional industrial interdependence and not simply the analysis of a higher or lower concentration of one industry compared to the others.

In the pre-crisis European countries considered we are able to identify nine different macro-regional patterns. Three of them are based on different combination of manufacturing industries and are located respectively in Southern Germany; Centre-Northern Italy and North-Eastern France; Eastern Germany and English Midlands. Two metropolitan patterns focus respectively on advanced services and on a mix of services and strategic manufacturing. Two further patterns covering most of Mediterranean and Atlantic regions share a common strength in the construction industry and the agri-food value chain. The remaining two patterns rely respectively on a more- and less advanced form of tourism industries.

The merging of the maps of robots with the industrial patterns highlights some major finding. The only macro-region 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 shows a declining growth rate, while manufacturing French regions appear to lack stock and not to increasing 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.

Innovation indicators and regional economic performances provide some further insights on the relationships between industrial patterns and robot penetration. We do not find a straightforward association between robot adoption and knowledge capital and/or technological levels of regions. For example, high endowment of human capital and R&D do not necessarily characterize regions rich robots nor those on the path of a rapid adoption, while regions high in stock are associated with higher patenting capacity.

Secondly, we find that a large manufacturing base is undoubtedly an advantage for substantial adoption of robot, but it is not a sufficient condition, nor a necessary one as proven by counterexamples. Preliminary evidence suggests exploring further the idea, that if any, there is a positive correlation between employment growth and development of advanced manufacturing, which is pushing many underperforming regions to adopt robots to a faster pace. However, any empirical exercise should take into account the idiosyncratic nature of regional systems, which do not represent simply different starting conditions, but they hide profound differences in the mechanisms at work.

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Appendix A

Data crosswalk

IFR uses industry codes in accordance with ISIC Rev. 4., while EUROSTAT SBS uses NACE Rev. 1.1 from 1995 to 2007 and NACE Rev.2 beginning from 2008. We first convert the NACE Rev. 1.1 data to NACE Rev. 2 using the approximate correspondence table provided by OECD (2012). Then, to match the EUROSTAT SBS and IFR data we use a conversion matrix constructed using the two-digit level of the NACE Rev. 2 and ISIC Rev. 4 industry classifications (at two-digit level, these two classifications coincide). For some of the 18 industries, IFR provides data at a more disaggregated level than two-digit. However, for these industries, EUROSTAT SBS only provides data at two-digit level.

Table A1. Correspondence table - NB: we use 15 industries (first column) and the last three columns show the correspondence between these 15 industries and the other industries classifications

CGGN CODE	Description	ISIC Rev. 4 code (IFR)	NACE Rev. 1 (SBS)	NACE Rev.2 (SBS)
1	Mining and quarrying	C-Mining and quarrying	C	B
2	Food and beverages	10-12-Food and beverages	DA15	C10+C11+C12
3	Textiles	13-15-Textiles	DB+DC	C13+C14+C15
4	Wood and furniture	16-Wood and furniture	DD	C16
5	Paper	17-18-Paper	DE	C17+C18
6	Plastic and chemical products	19-22-Plastic and chemical products	DF+DG+DH	C19+C20+C21+C22
7	Glass, ceramics, stone, mineral products (non-auto)	23-Glass, ceramics, stone, mineral products (non-auto)	DI	C23
8	Metal	24-28-Metal	DJ+DK	C24+C25+C28
9	Electrical/electronics	26-27-Electrical/electronics	DL	C26+C27
10	Automotive	29-Automotive	DM34	C29
11	Other vehicles	30-Other vehicles	DM35	C30
12	All other manufacturing branches	91-All other manufacturing branches	DN	C31+C32+C33
13	Electricity, gas, water supply	E-Electricity, gas, water supply	E	D+E
14	Construction	F-Construction	F	F
15	Services	P-Education/ research/ development + 90-All other non-manufacturing branches	G+H+I+K	G+H+I+J+L+M+N

Table A2. Cookbook values for featured industries whose SOM cookbook variance is higher than the average

Nace code	NACE description	1	2	3	4	5	6	7	8	9
DA15	Manufacture of food products and beverages	0.031	0.032	0.035	0.013	0.032	0.048	0.025	0.024	0.044
DG24	Manufacture of chemicals and chemical products	0.012	0.005	0.007	0.014	0.013	0.010	0.036	0.016	0.019
DJ28	Manufacture of fabricated metal products, except machinery and equipment	0.020	0.018	0.027	0.012	0.030	0.032	0.022	0.047	0.056
DK29	Manufacture of machinery and equipment n.e.c.	0.017	0.013	0.011	0.015	0.031	0.018	0.033	0.077	0.042
DL31	Manufacture of electrical machinery and apparatus n.e.c.	0.009	0.003	0.004	0.008	0.012	0.010	0.014	0.035	0.016
DM34	Manufacture of motor vehicles, trailers and semi-trailers	0.009	0.003	0.006	0.007	0.015	0.019	0.037	0.053	0.019
F45	Construction	0.091	0.180	0.301	0.074	0.074	0.156	0.042	0.042	0.116
G52	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	0.196	0.143	0.131	0.158	0.173	0.149	0.122	0.141	0.113
H55	Hotels and restaurants	0.131	0.187	0.083	0.094	0.085	0.072	0.060	0.056	0.057
I64	Post and telecommunications	0.023	0.012	0.004	0.028	0.019	0.013	0.049	0.014	0.010
K72	Computer and related activities	0.017	0.015	0.004	0.041	0.017	0.013	0.025	0.017	0.014
K74	Other business activities	0.137	0.098	0.097	0.220	0.149	0.117	0.199	0.137	0.112

Figure A1. SOM feature map for 4 industries

