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Identifying Clusters as Local Innovation Systems

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Abstract
This paper introduces an indicator for identifying innovation clusters that transcend traditional sectoral taxonomies and integrate the creation and use of knowledge in regional economic systems. Such clusters can be expected, based on the literature, to provide fertile ground for feedback mechanisms between knowledge supply and demand, hence contributing to circular cumulative growth dynamics through interactive learning. However, when it comes to operationalising the study of innovation, the creation and use of knowledge have been treated as distinct processes in related work. It is this gap that this paper seeks to address. Applying principal component analysis on location quotients of manufacturing employment data and patent microdata for 152 EU regions, we generate a mapping of co-located innovation-related activity that highlights the complex techno-economic structures of regional economies. Our analysis reveals clusters which include industries traditionally labelled as 'high-tech', as well as clusters that reflect centuries-old trajectories of geographically concentrated production specialisation. This research sheds new light on the co-location of innovation-related activity in regional economies and provides insights for policymakers and practitioners seeking to foster innovation and economic development in the context of evolving knowledge and production eco-systems.

Keywords Innovation · Clusters · Agglomeration · Patenting · Manufacturing

Introduction

This paper aims to address a gap in the literature studying innovation clusters by introducing an indicator which incorporates two phases of economic activity that have been treated as distinct in related studies: the creation of knowledge and the use

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of knowledge in production or, to put in Schumpeterian terms, the 'invention' phase and the 'innovation and diffusion' phase.

By creating an indicator which captures clustering in both patents and manufacturing employment, we attempt to depict the presence of a context which has the potential to serve as a fertile context for interactive learning (Asheim, 2001; Lundvall, 1985, 1992a), where knowledge exploration can co-exist, and co-evolve, with knowledge exploitation. Such a context incorporates both the 'formal' and the 'informal' types of innovation processes, and the complementarity between the two can be expected to provide potential for the enhancement of regional competitiveness (Isaksen & Nilsson, 2011a; Karlsen et al., 2011).

Previous empirical attempts to operationalise the cluster concept have centred on inter-industry linkages based on employment and establishment co-location, skill use, and supplier relationships via input–output measures (Czamanski & Ablas, 1979; Delgado et al., 2014; European Cluster Observatory, 2014a; Feser & Bergman, 2000).[1]

Porter (2003) identified clusters based on the statistically significant pairwise locational correlation between industries, which indicates industry relatedness. Ellison et al. (2010) examined a broad range of Marshallian forces shaping co-agglomeration using pairwise indices. While this methodology allows for the incorporation of multiple dimensions of cluster dynamics, the study of pairwise co-agglomeration limits the scope of cross-sectoral co-location that can be captured. Delgado et al. (2016) built on the aforementioned work and developed a novel cluster algorithm that incorporated measures of inter-industry linkages captured by co-location patterns, input–output links, and similarities in labour occupations. This approach has been used in the U.S. Cluster Mapping Project. As the authors noted, however, their methodology did not explicitly account for knowledge linkages.

Delgado (2020) underlined the need to account for the colocation of innovation and production in clusters and developed a methodology to measure it *ex post* in the cases

[1] It is worth noting that, apart from literature on cluster mapping and categorisation, a significant body of work focuses on examining different characteristics of specific cluster cases. This includes work by Saxenian (1996), who offered a comparative study of the evolution of the clusters in Silicon Valley and Route 128. Klepper (2010), using mainly data on firm entry and spinoffs, compared and contrasted the processes of emergence and growth in the Silicon Valley and Detroit clusters. Hervás-Oliver & Albors-Garrigós (2007) obtained data on resources and capabilities for firms belonging to two Italian and Spanish ceramic tile clusters and proceeded to examine their link to performance as measured by indicators related to financial data. Bittencourt et al. (2022) examined the cases of a Brazilian and French agribusiness cluster and underlined the importance of factors such as the establishment of a collective strategy and structured networks. Giuliani (2005),when studying three wine clusters in Italy and Chile via the use of network analysis, underlined that only a small subset of companies within a cluster both contributed to and benefited from localised knowledge spillovers. This confirmed the view that geographical proximity per se is not necessarily conducive to externalities linked to innovation (Boschma, 2005), and also that knowledge diffusion within clusters may lead to unequal outcomes, depending on the network structure of clusters (Cowan & Jonard, 2004; Morrison et al., 2013). Network structure, along with firm level characteristics and the industry life cycle phase, according to Ter Wal & Boschma (2011) are three main factors that form the context of interrelated dynamics which underpin the evolution of clusters. Along these lines, a range of recent case study work has placed focus on the factors impacting the evolution of traditional industry clusters in China (Fu et al., 2020; He et al., 2023).

of U.S. clusters defined by the aforementioned model. It is this dimension that our methodology seeks to introduce by explicitly measuring the colocation of innovation and production. To our knowledge, there has been no previous attempt to define clusters based on patterns of colocation of patenting and manufacturing. Our approach is, therefore, differentiated by its attempt to study the role of clusters that are not limited to production-related concentration but combine innovation and production.

Within this context, we can expect the presence of spillovers which may vary in direction, e.g. going back and forth between different modes of innovation across the innovation chain, which in the work of Srholec and Verspagen (2012) are identified as four distinct ‘ingredients’ of innovation strategies: research, user, external, and production. Spillovers may also occur between producer and final or intermediate user. Changes in intermediate demand contribute, according to Lorentz and Savona (2008), along with technical change, to the evolution of economies’ structural change and, consequently, to macroeconomic growth. Our indicator seeks to embody these circular cumulative growth dynamics based on the interaction between knowledge supply and demand.

By introducing a cluster-mapping approach which is free of any a priori assumptions regarding the types of activities that are ‘expected’ to be co-located, we allow for cluster patterns to emerge organically from our data and cut across different sectors, while also overcoming artificial boundaries between the generation of knowledge and the use of said knowledge in production. With the use of patent-micro-data, our aim is to capture concentration patterns that tend to have knowledge at their core, moving away from a strict focus on industry-related metrics. The cluster indicator that will be constructed will point towards the presence of a cognitive context which can be expected to be conducive to the generation, diffusion and absorption of innovation.

Literature Review

Attempting to incorporate the process of innovation in any type of economic analysis presents a fundamental challenge, since it is a broad and rather fluid concept[2] whose only defining characteristic, as Schumpeter (1947, p. 151) noted, is ‘simply the doing of new things or the doing of things that are already being done in a new way’.

We seek to systematise the related literature by underlining three basic dimensions of economic and innovation activity we seek to capture with our cluster indicator.

Agglomeration Dynamics

Marshall’s (1890) work on local spillovers, which underlined the importance of positive externalities between agglomerated firms belonging to the same sector,

[2] As Carayannis and Grigoroudis (2014) noted, innovation is often viewed as ‘inherently impossible to quantify and to measure’, mainly due to its many qualitative aspects.

identified agglomeration as a major factor influencing innovation and economic growth, based inter alia on the 'industrial atmosphere' present in a specific location, where the 'secrets of industry are in the air'. Utilising patent data, Jaffe (1986) identified the presence of localised R&D spillovers and their potential impact on firms' knowledge generation and profitability. The innovation systems approach (Freeman, 1987; Lundvall, 1992a, b; Nelson, 1993) draws on the concept of Marshallian externalities, but emphasised that a variety of actors affect the patterns of production, diffusion, and use of knowledge in economic activity within a specific geographic location, with its focus increasingly placed on the regional level (Asheim et al., 2005). The literature on clusters, which has grown rapidly following the influential work of Porter (1990, 1998), also underlined the role of the region as a key driver of growth and innovation due to localised spillovers, as do similar conceptual frameworks such as 'learning regions' (Morgan, 1997) and 'innovative milieux' (Aydalot, 1988). All the aforementioned terms are applied to illustrate a local context that favours the development of a learning-based economy (Doloreux & Parto, 2004). Focusing on geographically concentrated activity, therefore, can be viewed as the first step in the attempt to detect systems of enhanced innovation and productivity dynamics.

Coexistence of Knowledge Creation and Use

The second step is the identification of a local context where the creation and use of knowledge coexist. Traditionally, invention and innovation were often viewed as parts of a linear process, where one step distinctly follows the other. However, as Kline and Rosenberg (1986) noted, these two phases of the innovation cycle generate feedback mechanisms, referred to by Lundvall (1992a, b) as interactive learning between producers and users of knowledge. To return to Schumpeter's aforementioned quote, doing new things may induce new ways, and vice versa. Along those lines, Cooke (2005, p.3) described the regional innovation systems as 'interacting knowledge generation and exploitation subsystems' at the regional level. As is the case with innovation, however, 'knowledge' is not a uniform concept. Polanyi (1958) distinguished between 'tacit' and codified knowledge, pointing out that knowledge is often not explicitly articulated but, like Marshall's industry secrets, may exist 'in the air'. Jensen et al. (2007) used this distinction to contrast two corresponding modes of innovation: the Science, Technology and Innovation (STI) mode, which is 'based on the production and use of codified scientific and technical knowledge' and the Doing, Using and Interacting (DUI) mode, which 'relies on informal processes of learning and experience-based know-how' (p. 680). The authors found that firms that combine both modes appear to be more innovative, while Isaksen and Nilsson (2011a, b) drew similar conclusions, noting that the complementarity of 'formal' and 'informal' types of innovation potentially contribute to increased innovative capacity and competitiveness at the level of regional innovation systems. So far, most related empirical research on the operationalisation of innovation systems — a term which we will henceforth use interchangeably with the term ‘cluster’ — has failed to account for the combination of these two modes of innovation (Cruz & Teixeira, 2010; Lazzeretti et al., 2014).

Technology Relatedness and Spillovers

A third step in the identification and examination of clusters is to decide on how narrowly or widely to frame the cognitive space of such systems of innovation and production in terms of technologies and industries. Marshall’s aforementioned influential work — which was later built upon by Arrow (1962) and Romer (1987) — underlined the importance of externalities between firms belonging to the same sector. Jacobs (1969), on the other hand, emphasised the role of knowledge flows between different sectors mainly within the context of urbanisation economies. Similarly, Jaffe et al. (1993, p. 596) observed that knowledge spillovers are probably ‘not confined to closely related regions of technology space’. Literature findings have pointed towards the presence of both specialisation and diversification effects on regional economic performance (Beaudry & Schiffauerova, 2009). In regard to the evolution of technologies, Dosi’s (1982) work has focused on the path dependent nature of technological change, with recent studies suggesting that regions branch into industries related to their existing activities (Corradini & Vanino, 2022; Neffke et al., 2011). Heimeriks et al. (2018) noted that the growing global technological base increases technological diversity, but also linkages between technologies, hence leading to increased complexity of knowledge ecosystems. Balland et al. (2019) attempted to depict technology relatedness and complexity in EU regions via the use of network-based techniques on patent data. Buccellato and Corò (2019) also depicted relatedness and complexity, but in terms of statistical industry classifications. When it comes to the methodological implications of the diminishing importance of fixed traditional sectoral boundaries on cluster mapping, Martin and Sunley (2003) noted that a significant limitation of ‘top-down’ cluster mapping exercises has to do with the fact that they study concentrations of economic activity on an industry-by-industry basis, hence disregarding linkages across industries which are central to the cluster concept. Along these lines, Srholec and Verspagen (2012, p. 1248) warned against a ‘mechanistic replication of taxonomies based on sectoral data’.

Operationalising the Literature

The indicator developed and presented in this paper incorporates the three aforementioned dimensions of the related literature as follows: the spatial agglomeration dimension is introduced via the use of location quotients, in order to capture the concentration of activity. The combined use of data on patenting and manufacturing helps embody different stages of the innovation process and consequently both formal and informal modes of interactive learning. And, finally, the use of principal component analysis on pooled data allows for the emergence of patterns of colocation that transcend traditional taxonomies of patenting and manufacturing activity, hence allowing for the inclusion of different branches that form part of the complex structure of innovation ecosystems.

Methodology: Patterns of Manufacturing and Patenting Co-Location

The first step of our analysis is to generate clusters for the year 2010,[3] based on the co-located concentration of manufacturing and patenting activity at the regional (NUTS 2) level. For manufacturing data, we utilise Eurostat's Structural Business Statistics database. For patents, we use the OECD REGPAT database, which contains detailed regionalised patent data.[4]

We use the location quotient (LQ) as an index of spatial concentration. The location quotient is an analytical statistic which is often used in order to measure the concentration of a certain economic activity in a region compared to a broader geographical entity. The European Cluster Observatory has applied this method in order to define employment-based clusters in NUTS regions in Europe (European Cluster Observatory, 2014b; European Commission, 2007). The widespread use of this type of methodologies by researchers in related fields is facilitated by the relatively easy access to employment data. Apart from its simplicity, the location quotient has several advantages when it comes to spatial pattern analysis (Lu, 2000), including its ability to depict concentration in relation to a different 'standard' area, in our case different counties. In the context of the present study, the LQ is particularly appropriate for an additional reason: it is a metric which is comparable across different types of data, in this case data on employment and patenting. The construction of the patent LQs was implemented based on the patent data of the OECD REGPAT database which have been linked to regions according to the inventors' and applicants' addresses. The patent applications under examination in the present paper are the ones made to the European Patent Office. Regarding the year, address, and way of counting each patent application, certain choices were made, in accordance to the related guidelines set out in the OECD Patent Statistics Manual (OECD, 2009). The year was defined according to the priority date, which indicates the first date of filing of the patent application and therefore can be considered the one closest to the actual invention date. The address considered was that of the inventor, since it gives information about innovation activity in the specific region, while the applicant's address, which refers to the location of the company that owns the patent, may be in a different country. In cases of patents with multiple inventors, the method used was that of fractional counting, which attributes to each region the percentage which reflects its contribution to the patent. Equal weights were assigned to each contribution.

Manufacturing employment LQ[5] [6]:

$$\frac{\textit{Manufacturing subsector regional employment}}{\textit{Manufacturing total regional employment}} \Big/ \frac{\textit{Manufacturing subsector EU employment}}{\textit{Manufacturing total EU employment}}$$

Patent LQ:

[3] The choice of year was made in order to allow for the use of the indicator in econometric analysis which may examine potential links between cluster presence and different aspects of regional performance in recent years.

[4] An in-depth presentation of the OECD REGPAT database was provided by Maraut et al. (2008)

[5] Based on the Statistical Classification of Economic Activities NACE, Rev.1.1 of the European Union.

[6] International Patent Classification. Detailed descriptions of IPC classes are available at http://web2.wipo.int/ipcpub

$$\frac{\text{IPC class regional patents}}{\text{total regional patents}} \Big/ \frac{\text{IPC class EU patents}}{\text{total EU patents}}$$

Having produced a set of 129 LQs for EU-15 NUTS 2 regions[7] [8], we proceed to implement principal component analysis (PCA) in order to capture the co-location of different types of activity.

PCA is a method for reducing the dimensions of a multivariate dataset while preserving a significant portion of its variability by producing a set of uncorrelated factors (principal components) which are linear combinations of the initial correlated variables. In the context of studying innovation dynamics, this methodology has been utilised recently by Kleszcz (2021) in order to aggregate the dimensions of the indicators constituting the European Innovation Scoreboard. PCA provides a particularly good fit to the theoretical underpinnings of our approach, since we seek to produce cluster indicators based on patterns that emerge organically from the data and not on a priori assumptions regarding cluster composition (Jolliffe & Cadima, 2016), while also having a clear view of the most important elements that comprise each cluster.

Given a dataset X consisting of n observations and p variables, the goal of PCA is to find the k principal components that maximise the variance of the data. The principal components are computed by finding the eigenvectors of the covariance matrix of X, and the amount of variance explained by each principal component is equal to the corresponding eigenvalue.

The transformed data can be represented by $Y = X[V_1, V_2, \ldots, V_k]$, where Y is a $n \times k$ matrix and $V_1, V_2, \ldots, V_k$ are the eigenvectors of the covariance matrix of X, arranged in descending order of eigenvalue. The amount of variance explained by the i-th principal component is equal to the corresponding eigenvalue, λ_i.

In order to generate the factors, we used Bartlett's method (Bartlett, 1937) which minimises the sums of squares of factors using least squares. It has been argued in the relevant literature that this process produces factor scores that are highly correlated with their related factors (Gorsuch, 1983) and are unbiased (Hershberger, 2005). We applied the Kaiser-Gutman criterion (eighenvalues > 1) in order to select the number of principal components.

We implemented a three-step PCA: in the first step, we performed PCA on standardised LQ's in each IPC class category. In the second step, we performed PCA on all factors generated via Bartlett's method in the first step, and, in the third, final step (whose output is presented in Table 1), we pooled the new Bartlett's patent factors generated with standardised manufacturing employment LQ's, in order

[7] NUTS 2 is the level of analysis used, inter alia, by Ketels and Protsiv (2013) and Rodríguez-Pose and Comptour (2012) in their work with Cluster Observatory data. While there is, obviously, no definitive answer regarding the choice of spatial unit for the mapping of clusters, choosing a smaller unit (e.g. NUTS 3) presents certain challenges since, as Porter (2003) noted, regions with low (or zero) levels of employment in some industries may lead to artificially high rates of correlation, therefore throwing off track the process of pattern identification.

[8] Regions with less than 200 total patents per year were filtered out, since in a region with few total patents, even one patent in a particular IPC class can lead to a very high LQ, which is not likely, however, to represent an actual concentration of patent activity.

Table 1 Cluster generation — PCA third step output

Rotated Component Matrix					
	Component				
	1	2	3	4	5
Manufacturing Employment LQ's					
Textiles	-0.1	0.3	0.1	0.7	-0.2
Wood	-0.3	0.6	-0.2	-0.3	-0.2
Chemicals	0	-0.3	-0.1	0.3	0.6
Rubber	0.4	0	0	0.4	-0.4
Basic Metals	0.5	0.4	-0.4	-0.2	0.1
Electrical equipment	0.6	0.2	0.4	-0.1	0.1
Fabricated Metals	0.2	0.7	0	0.2	-0.1
Computer	0.3	0	0.8	-0.1	0.2
Motor Vehicles	0.6	0	0	0.1	0
Bartlett factor scores for patents					
Performing operations & transporting, mechanical engineering, chemistry & metallurgy	0.7	-0.1	-0.2	-0.3	-0.3
Textiles	0	-0.2	-0.2	0.8	0.1
Electricity	-0.2	-0.1	0.8	-0.1	-0.1
Chemistry & Metallurgy	0	0	0	-0.2	0.8
Fixed construction, mechanical engineering	0	0.8	0	0	0

Extraction Method: Principal Component Analysis

Rotation Method: Varimax with Kaiser Normalisation

to implement PCA to produce 5 factors capturing co-located activity, henceforth referred to as cluster indicators. We applied a cut-off value of 0.5 (as indicated by the highlighted values) and labelled these indicators based on their composition (Table 2) as follows: motor and electronics, wood and metal, computer, textiles, chemicals.

In Fig. 1, we illustrate the cumulative percentage of the sample's variance captured by our first 5 principal components, which is 60%. This percentage is close to that of the principal components chosen, for instance, in the aforementioned work of Kleszcz (2021)−68%. It should be noted, however, than in the context of the present paper, the primary goal is not to maximise the variance explained by the specific principal components, but rather to interpret the patterns of co-location depicted by them.

In Fig. 2, we illustrate the 5 principal components via a parallel coordinates plot, a well-established tool for visualising multidimensional data (Xyntarakis & Antoniou, 2019). The plot reveals that no particular region exhibits exceptionally high or low scores across all indicators, and no clear correlations between variables are observed. This is consistent with the orthogonal nature of principal components, which capture the maximum amount of variation in the original data while minimising the correlation between them.

In Table 2, we present the descriptive statistics for the cluster indicators. Certain elements that stand out are that mean and median values are close to zero in all

Table 2 Descriptive statistics for cluster indicators

Clusters	Obs	Mean	Median	Standard deviation	Minimum value	10th percentile	90th percentile	Maximum value
Motor and electronics	152	6	0	87	−227	−123	159	219
Wood and metal	152	1	0	84	−253	−116	132	251
Computer	152	−1	0	85	−320	−131	120	296
Textile	152	6	0	82	−227	−112	123	275
Chemical	152	−3	0	87	−268	−120	119	271

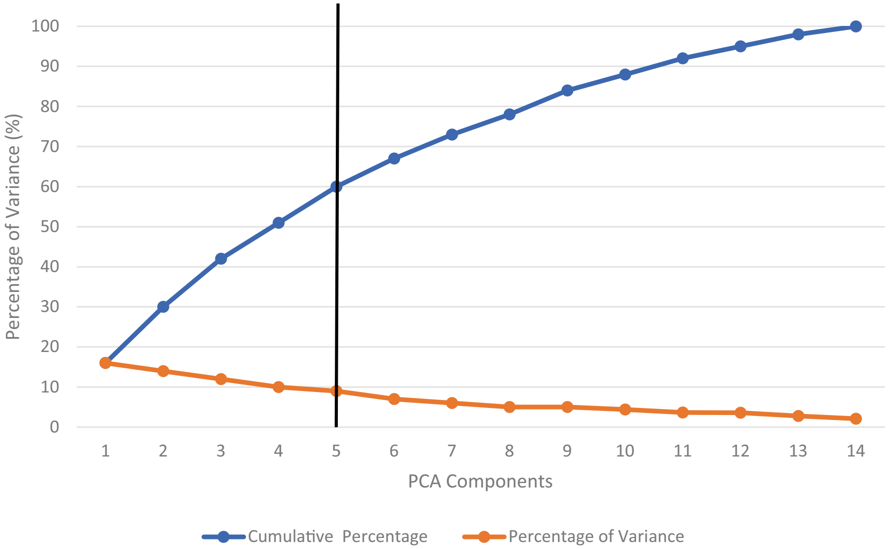

Fig. 1 Percentage of sample variance explained by principal components

cluster indicators, while the standard deviation is particularly high, ranging from 82 to 87. This indicates high level of disparities among regions when it comes to cluster scores, and in the next section, we will examine more closely the nature of these disparities.

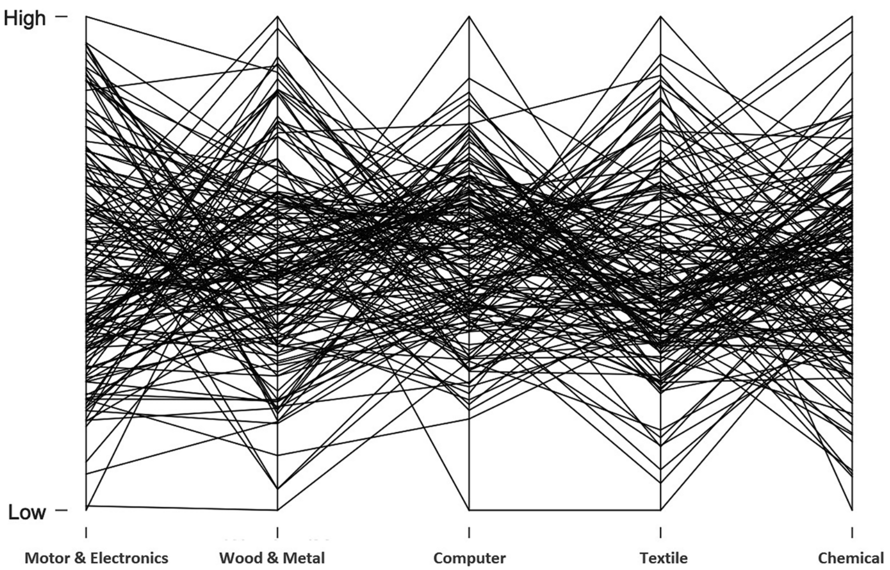

Fig. 2 Parallel coordinates plot for principal components

Table 3 presents the detailed cluster composition, based on the first two steps of our PCA. The picture that emerges is one that presents clear elements of the ‘related variety’ and ‘complexity’ concept, i.e. clusters that are not narrowly defined in industry terms but include activity in different industries that are connected in terms of research and production.

In the component we label ‘Motor & Electronics Cluster’, we observe high loadings from two employment categories (manufacture of motor vehicles and manufacture of electrical equipment) and three patent categories (performing operations and transporting, mechanical engineering, chemistry, and metallurgy). Our ‘Computer Cluster’ and ‘Textile Cluster’ components also contain high loadings from three different types of patents (performing operations and transporting, physics, electricity in the computer cluster and performing operations and transporting, chemistry and metallurgy, textiles and paper in the textile cluster). In the ‘Wood & Metal’ and ‘Chemical’ components, we see two patent categories loading highly (fixed construction and mechanical engineering in the wood cluster and chemistry and metallurgy, performing operations and transporting in the chemical cluster), as well as two employment categories in the case of the wood and metal cluster (manufacture of wood products, manufacture of fabricated metal products except machinery).

It is worth noting that in the textile cluster, which centres around an industry usually viewed as ‘traditional’, we observe a high loading of the patent component ‘Organic Macromolecular Compounds and their Composition’ which relates to the shift of the textile industry toward technical textile production, an area of rapid innovation in which Europe has a leading role (McCarthy, 2016).

Cluster Geography

After having produced these cluster indicators, we proceed to examine the spatial distribution of cluster scores, both when it comes to concentration patterns at the European and inter-regional level, but also in regard to specific high-scoring regions, in order to detect indications of the historical evolution of industry specialisation.

In order to examine the degree of EU-wide spatial concentration of our cluster indicator scores, we first utilise the Moran’s coefficient, after having created a first-order queen contiguity weight matrix.[9] Moran’s I is a statistic used to measure spatial autocorrelation, i.e. the correlation of characteristics of proximal locations, and its values range from −1 (perfect dispersion) to 1 (perfect concentration). It is defined as:

$$I = \frac{N}{W} \cdot \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2}$$

where:

- N: the number of spatial units indexed by i and j
- x: the variable of interest

[9] I.e. regions are considered neighbouring when they share a border

Table 3 Cluster composition

Motor and electronics cluster

Employment:
C29 Manufacture of motor vehicles, trailers and semi-trailers
C27 Manufacture of electrical equipment

Patents:

B21 MECHANICAL METAL-WORKING WITHOUT ESSENTIALLY REMOVING MATERIAL; PUNCHING METAL

B23 MACHINE TOOLS; METAL-WORKING NOT OTHERWISE PROVIDED FOR

C21 METALLURGY OF IRON

C22 METALLURGY; FERROUS OR NON-FERROUS ALLOYS; TREATMENT OF ALLOYS OR NON-FERROUS METALS

C23 COATING METALLIC MATERIAL; COATING MATERIAL WITH METALLIC MATERIAL; CHEMICAL SURFACE TREATMENT; etc

F01 MACHINES OR ENGINES IN GENERAL; ENGINE PLANTS IN GENERAL; STEAM ENGINES

F02 COMBUSTION ENGINES; HOT-GAS OR COMBUSTION-PRODUCT ENGINE PLANTS

F04 POSITIVE-DISPLACEMENT MACHINES FOR LIQUIDS; PUMPS FOR LIQUIDS OR ELASTIC FLUIDS

Wood and metal cluster

Employment:
C16 Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C25 Manufacture of fabricated metal products, except machinery and equipment

Patents:

E02 HYDRAULIC ENGINEERING; FOUNDATIONS; SOIL-SHIFTING

E05 LOCKS; KEYS; WINDOW OR DOOR FITTINGS; SAFES

F24 HEATING; RANGES; VENTILATING

F25 REFRIGERATION OR COOLING; COMBINED HEATING AND REFRIGERATION SYSTEMS; HEAT PUMP SYSTEMS;
MANUFACTURE OR STORAGE OF ICE; LIQUEFACTION OR SOLIDIFICATION OF GASES

Computer cluster

Employment:
C26 Manufacture of computer, electronic and optical products

Patents:

B62 LAND VEHICLES FOR TRAVELLING OTHERWISE THAN ON RAILS

G06 COMPUTING; CALCULATING; COUNTING

H01 BASIC ELECTRIC ELEMENTS

H03 BASIC ELECTRONIC CIRCUITRY

Textile cluster

Employment:
C13 Manufacture of textiles

Patents:

B05 SPRAYING OR ATOMISING IN GENERAL; APPLYING LIQUIDS OR OTHER FLUENT MATERIALS TO SURFACES, IN GENERAL

B31 MAKING ARTICLES OF PAPER, CARDBOARD OR MATERIAL WORKED IN A MANNER ANALOGOUS TO PAPER; etc

B32 LAYERED PRODUCTS

B65 CONVEYING; PACKING; STORING; HANDLING THIN OR FILAMENTARY MATERIAL

C08 ORGANIC MACROMOLECULAR COMPOUNDS; THEIR PREPARATION OR CHEMICAL WORKING-UP; COMPOSITIONS BASED THEREON

Table 3 (continued)

Motor and electronics cluster
C09 DYES; PAINTS; POLISHES; NATURAL RESINS; ADHESIVES; etc
D02 YARNS; MECHANICAL FINISHING OF YARNS OR ROPES; WARPING OR BEAMING
D03 WEAVING
D04 BRAIDING; LACE-MAKING; KNITTING; TRIMMINGS; NON-WOVEN FABRICS
Chemical cluster
Employment:
C20 Manufacture of chemicals and chemical products
Patents:
C12 BIOCHEMISTRY; BEER; SPIRITS; WINE; VINEGAR; MICROBIOLOGY; ENZYMOLOGY; MUTATION OR GENETIC ENGINEERING
C07 ORGANIC CHEMISTRY
C01 INORGANIC CHEMISTRY
B01 PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL
B07 SEPARATING SOLIDS FROM SOLIDS; SORTING
B82 NANOTECHNOLOGY

- $\bar{x}$: the mean of x
- w_{ij}: a matrix of spatial weights with zeroes on the diagonal
- W is the sum of all w_{ij}

We observe (Table 4) moderate levels of concentration which are significantly higher in the case of the motor and electronics cluster.

Before examining the regional characteristics of the cluster indicators' geographical patterns, it is worth providing some context at the national level through a metric often used as a proxy for innovation 'input', namely expenditure on R&D spending. Figure 3 presents Eurostat data for two years: 2000 and 2010. What instantly stands out is a clear dichotomy between the so-called core and periphery countries of EU-15. The four southern countries (Greece, Italy, Spain, and Portugal) are the four worst performers, an observation which reflects the well documented gap in technological capabilities between core and periphery (Graebner & Hafele, 2020).

Turning our attention to the maps of NUTS 2, this observation is re-affirmed at a first glance, since it is easily discernible that regions with high motor and electronics

Table 4 Spatial autocorrelation of cluster indicator values

Cluster	Moran's I
Motor and electronics	0.45
Wood and metal	0.27
Computer	0.30
Textiles	0.23
Chemicals	0.25

all values are statistically significant after being randomised for 999 permutations

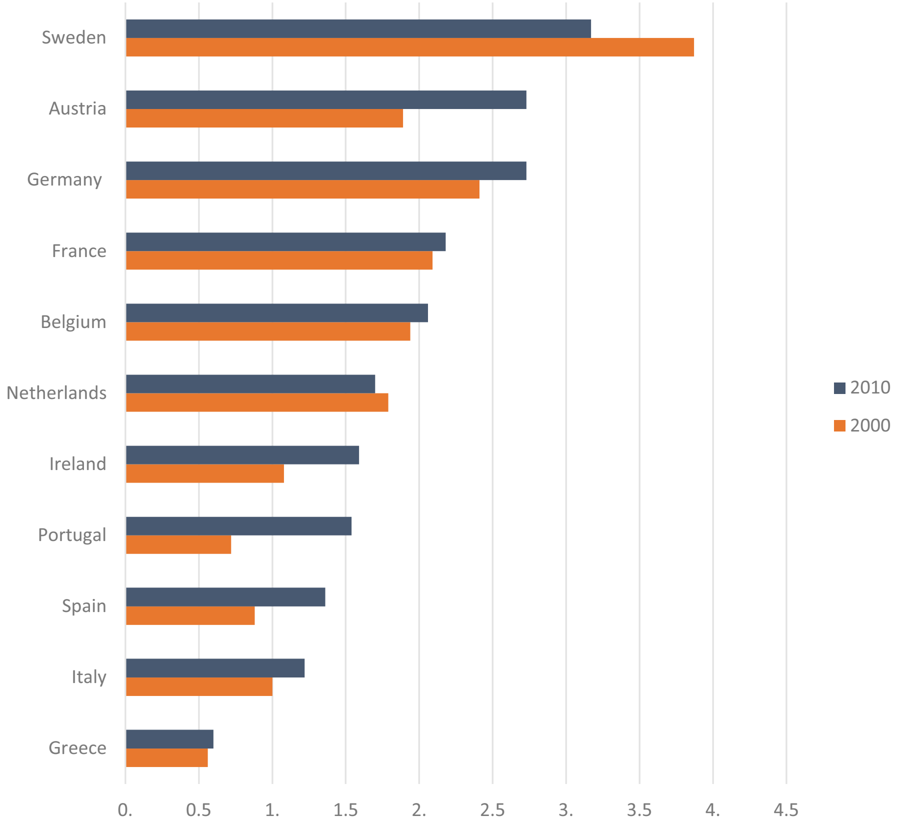

Fig. 3 Expenditure on R&D (percentage of GDP)

cluster scores are concentrated in Germany (Fig. 4). Other spatial patterns that stand out — albeit to a smaller degree — include the concentration of wood and metal in the Austria — Northern Italy wider region (Fig. 5), Computer in the south of the UK (Fig. 6), Textiles in Northern Italy (Fig. 7), and Chemicals in several Dutch regions Fig. 8).

In Table 5, we present the top-10 regions in each cluster according to their indicator score. As expected when observing the maps, in regard to the motor and electronics cluster, we can observe that 9 out of the 10 top scoring regions are in Germany, thus directly reflecting the country's dominance in the industry. Four of the top 10 motor and electronics cluster regions are present in other cluster top 10's as well: Mittelfranken in the computer cluster, Düsseldorf in the chemical cluster, Chemnitz in the textile cluster and Arnsberg — where the logistics hub of Dortmund is located — in the wood and metal cluster. In several of the other top regions, we find headquarters and/or plants of major automotive companies: Mercedes-Benz and Porsche in Stuttgart, Renault and PSA (maker of Peugeot, Citroën, DS, Opel, and Vauxhall) in Île de France, and Ford Europe in Köln.

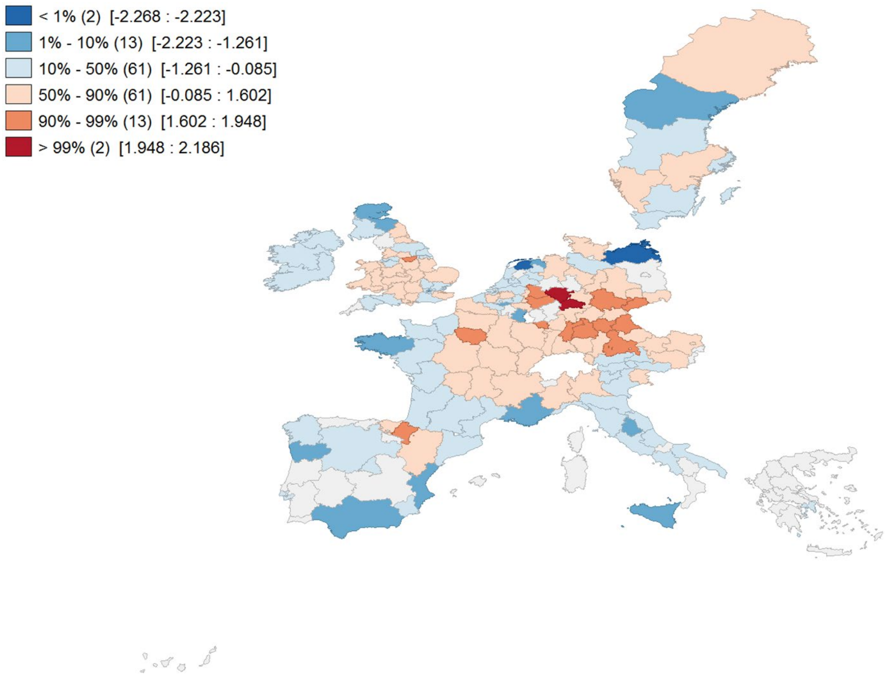

Fig. 4 Motor and electronics cluster

Regarding the wood and metal cluster, the presence of natural resources can be expected to be heavily connected to this type of activity. Norrland, for example, has been known throughout centuries as a region rich in resources (Hermele, 2013). It is worth noting that other top-scoring regions with traditions in steel industries such as Arnsberg and País Vasco have, in recent decades, branching towards related sectors (González, 2005; van Winden et al., 2010).

UK regions score highly in the computer cluster indicator. The top 3 regions are located in the UK and specifically in the area surrounding London (Surrey, East and West Sussex, Hampshire, and Isle of Wight, Essex). We can observe the presence of metropolitan centres in other top regions, such as Edinburgh (in Eastern Scotland) and Wien, as well as other established clusters of high-tech economic activity, such as Eindhoven (in the Noord-Brabant region).

When examining the top scoring regions in the textile cluster, one can observe trajectories of economic activity which, as in the case of wood and metal, date back centuries. In particular, Flanders (where the top 2 regions are located) has dominated the textile export market since 1200 and textiles from Lombardy (the region which is at number 5 on the list) constituted a significant part of the Levant trade (Chorley, 1987), while the region of Valencia was a centre for silk production since the eighth century (Boyd-Bowman, 1973).

Turning to the chemical cluster, Hainaut, the top scoring region, is where the first industrial production of ammonia soda based on the process patented by Ernest Solvay (co-founder of the chemicals giant Solvay) took place in 1864 (Aftalion, 2001). In the

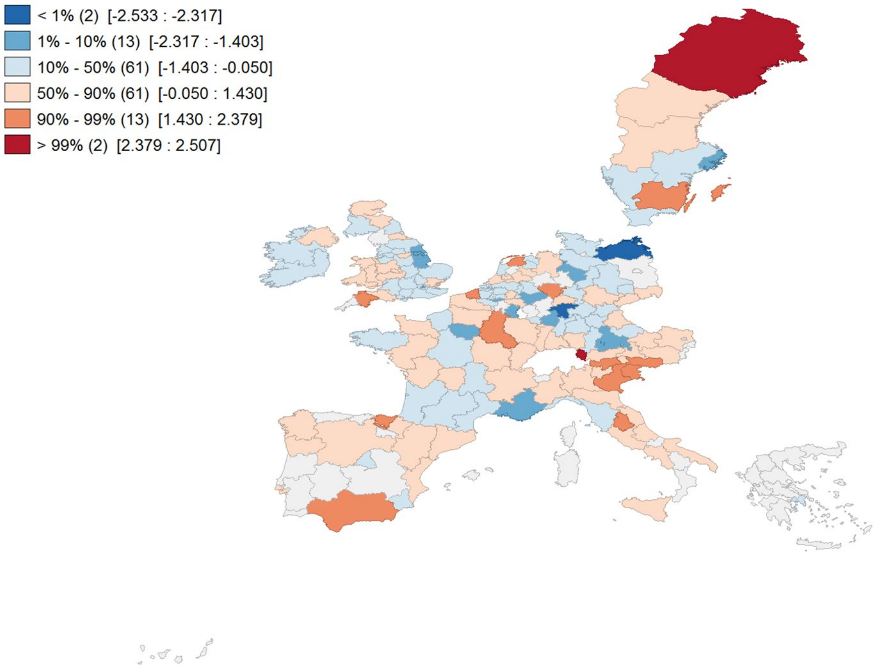

Fig. 5 Wood and metal cluster

top 10, we also find the Zuid-Holland region — where Rotterdam is located — and its neighbouring Utrecht region. As Smit notes (van den Bosch & Man, 2013), historically the accessibility of Rotterdam to huge vessels played a major role in the development of a petrochemical cluster (which included what was to become the Shell Pernis petrochemical complex), while later on — from the mid-1960s onwards — the location attracted basic chemical companies since 'oil products constitute the most important input for these industries'. They were followed by chemical companies and the subsequent development of a network of suppliers of related goods or services. Not all regions appearing in the top 10 lists are, of course, widely recognisable as hosts to significant innovation activity. Drenthe, which appears to have a high chemical cluster indicator is arguably such a case. However, the chemical cluster Emmen, a European leader in specialised chemistry, is located in the region and provides the base for facilities of globally competitive companies such as Teijin Aramid, DSM Engineering Plastics and Low&Bonar.

Cluster Characteristics

Region Characteristics

In Table 6, we proceed to examine a set of metrics for top-10 scoring technology-production clusters concerning gross value added (GVA), R&D spending, and

Table 5 Top cluster regions

Motor and electronics	Wood and metal	Computer	Textile	Chemicals
DEA5 – Arnsberg	SE33—Övre Norrland	UKJ2—Surrey, East and West Sussex	BE25—Prov. West-Vlaanderen	BE32—Prov. Hainaut
DE72 – Gießen	AT34 – Vorarlberg	UKJ3—Hampshire and Isle of Wight	BE23—Prov. Oost-Vlaanderen	DEB3—Rheinhessen-Pfalz
DEC – Saarland	ITD1 – Prov. Autonoma Bolzano/Bozen	UKH3 – Essex	ES52—Comunidad Valenciana	UKC1—Tees Valley and Durham
DEA2 – Köln	SE21—Småland med öarna	DE23 – Oberpfalz	NL21 – Overijssel	DEE—Sachsen-Anhalt
DE12 – Karlsruhe	ES21—País Vasco	UKM2—Eastern Scotland	ITC4 – Lombardia	NL33—Zuid-Holland
DE25 – Mittelfranken	DEA5 – Arnsberg	NL41—Noord-Brabant	FR72 – Auvergne	NL13 – Drenthe
DEA1 – Düsseldorf	BE25—Prov. West-Vlaanderen	NL21 – Overijssel	UKD3—Greater Manchester	NL42—Limburg (NL)
DED1—Chemnitz	AT21 – Kärnten	DE25 – Mittelfranken	PT11 – Norte	DED3—Leipzig
DE11 – Stuttgart	ITE2—Umbria	AT13 – Wien	DED1—Chemnitz	DEA1—Düsseldorf
FR1—Île de France	FR21—Champagne-Ardenne	IE02—Southern and Eastern	FR23—Haute-Normandie	NL31—Utrecht

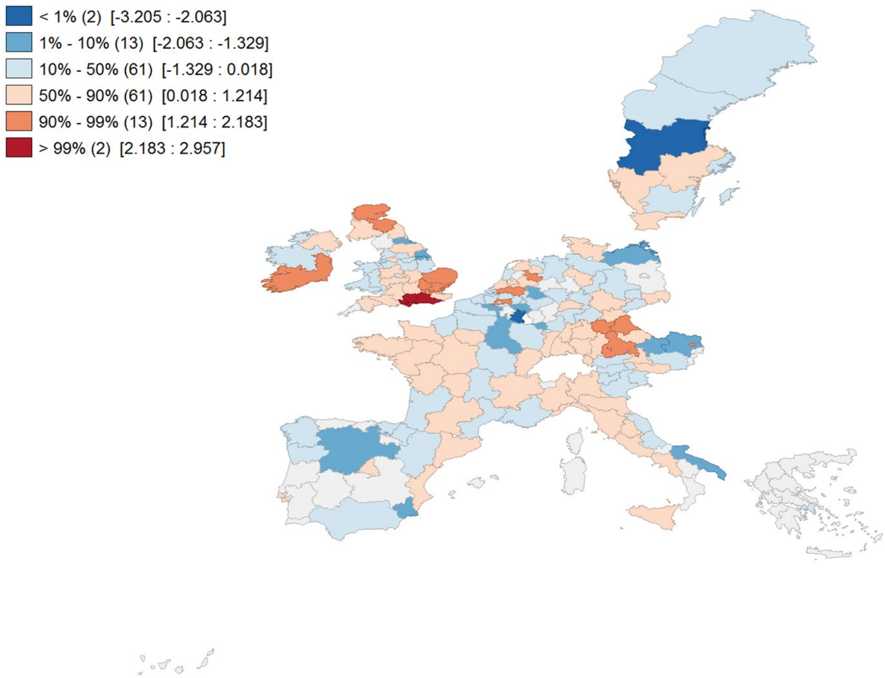

Fig. 6 Computer cluster

gross fixed capital formation (GFCF) and we compare the median values of the top regions' data with the median values of all the regions in our dataset.[10] GVA is often used as a metric for sectoral added value at the regional level (e.g. Montoya & de Haan, 2008), while R&D spending has been traditionally viewed as a proxy for 'innovation input' (Maclaurin, 1953), which tends to generate knowledge spillovers (Jaffe, 1986; Nelson, 1959). Such spillovers, Acs et al. (1994) argue, are more crucial for small firms. Finally, gross fixed capital formation is used to illustrate sectoral investment at the regional level (Stirböck, 2002).

Regarding our descriptive data, we observe that the regions that score highly in the motor and electronics cluster indicator tend to have significantly higher values in all metrics except those concerning the agricultural sector, indicating that this type of cluster is located in highly competitive regions.

On the contrary, regions with high wood and metal cluster scores appear to have significantly lower levels of GVA and GFCF in every sector apart from agriculture, as well as low levels of R&D spending. This is in accordance to the observations on resource-based clusters outlined in the first section, which point out that such economies risk falling victims to lock-in due to their focus on specific types

[10] The median is preferred to the average in order to minimise the effect of outliers.

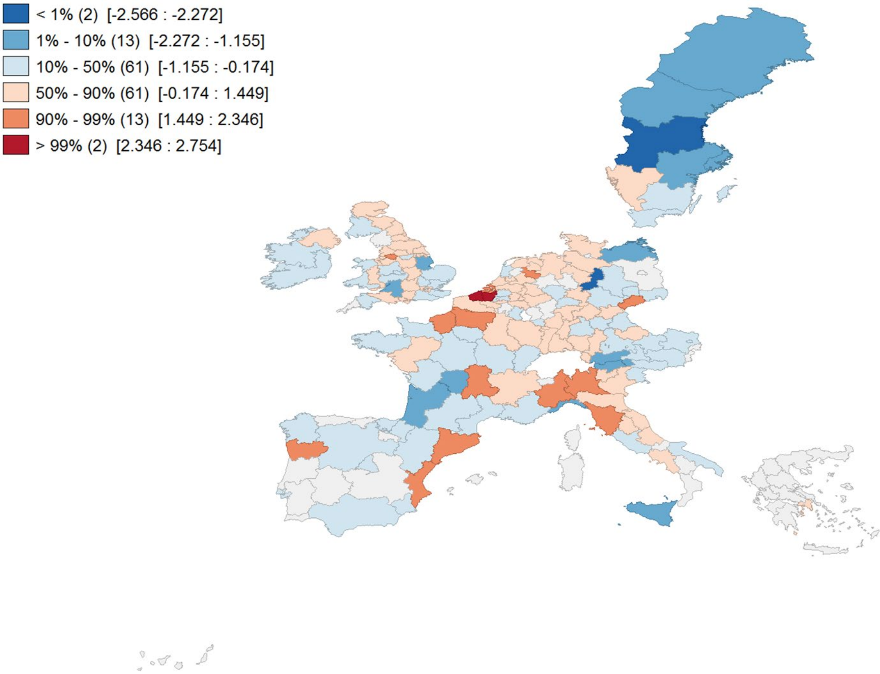

Fig. 7 Textile cluster

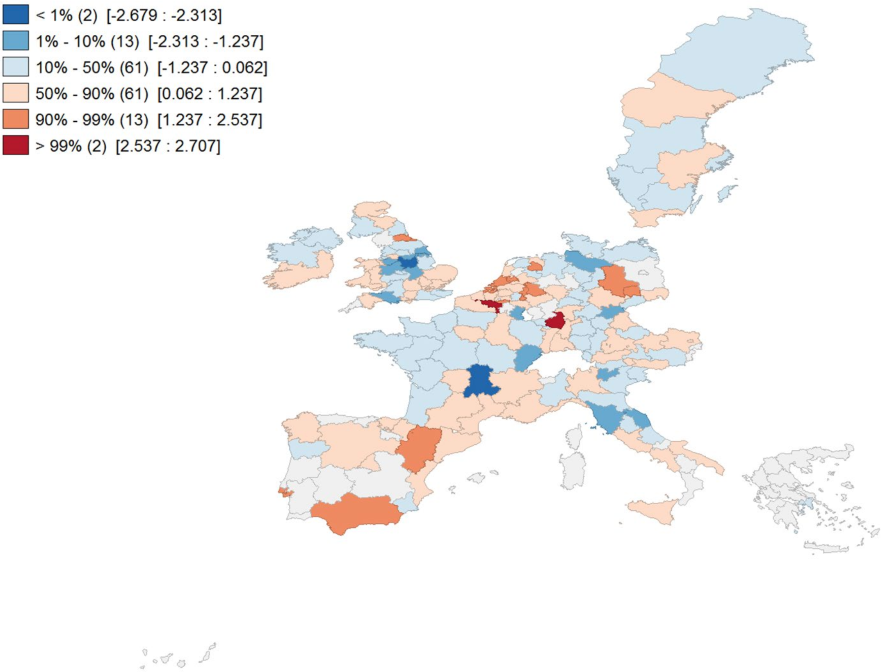

Fig. 8 Chemical cluster

Table 6 Top-10 regions' GVA, R&D, and gross fixed capital formation data

	TOTAL - Total - all NACE activities	A – Agricul-ture, forestry and fishing	C – Manufac-turing	G-I - Trade, transport, accommoda-tion and food service activities	J – Informa-tion and communic-ation	TOTAL - All sectors	BES - Business enterprise sector
Motor & Electronics Cluster							
DEA5 – Arnsberg	92636	296	24836	13798	1959	1.5	0.9
DE72 – Gießen	25600	136	6545	3836	498	2.2	1.2
DEC0 – Saarland	27262	47	6778	4398	926	1.5	0.5
DEA2 – Köln	135387	330	22126	20840	12527	3	1.3
DE12 – Karlsruhe	88781	241	22640	13138	6628	4.1	2.5
DE25 – Mittelfranken	52321	307	14067	7459	2283	3.5	2.6
DEA1 – Düsseldorf	162294	508	30101	29112	8080	1.8	1.4
DED1 - Chemnitz	29874	253	7142	4599	673	1.8	1
DE11 – Stuttgart	143964	530	49030	18908	6310	6.1	5.6
FR10 - Île de France	549113	593	37440	98965	57534	3	2
EU region median	35909	501	5592	6701	926	1	0.8
Top regions median	90709	302	22383	13468	4296	2.6	1.4
% Difference	153%	-40%	300%	101%	364%	80%	81%
Wood & Metal Cluster							
SE33 - Övre Norrland	17347	484	2178	2478	586	2.3	0.4
AT34 – Vorarlberg	11978	70	3353	2748	152	1.4	1.3

Table 6 (continued)

	TOTAL - Total - all NACE activities	A – Agricul-ture, forestry and fishing	C – Manufac-turing	G-I - Trade, transport, accommoda-tion and food service activities	J – Informa-tion and communic-ation	TOTAL - All sectors	BES - Business enterprise sector
ITH1 – Bolzano/ Bozen	17164	812	1989	4720	354	0.6	0.4
SE21 - Småland med öarna	23631	801	5592	4299	659	1.4	1.1
ES21 - País Vasco	60151	428	14262	11961	2023	2.1	1.6
DEA5 – Arnsberg	92636	296	24836	13798	1959	1.5	0.9
BE25 - Prov. West-Vlaanderen	32939	678	6336	6770	629	1.1	:
AT21 – Kärnten	14774	289	2742	3346	250	2.8	2.4
ITE2 - Umbria	19742	443	3043	4058	436	0.9	0.3
FR21 - Champagne-Ardenne	31872	2940	5341	5232	350	0.7	0.5
EU region median	35909	501	5592	6701	926	1	0.8
Top regions median	21686	463	4347	4509	511	1.4	0.9
% Difference	-40%	-7%	-22%	-33%	-45%	-2%	17%
Computer Cluster							
UKJ2 - Surrey, East and West Sussex	75786	300	5159	14000	4430	1.7	1.3
UKJ3 - Hampshire and Isle of Wight	51187	245	5412	9645	4194	2.7	2
UKH3 – Essex	37153	214	4071	8175	1104	2.2	2.1
DE23 – Oberpfalz	31108	384	10250	4162	483	:	2

Table 6 (continued)

	TOTAL - Total - all NACE activities	A – Agricul-ture, forestry and fishing	C – Manufac-turing	G-I - Trade, transport, accommoda-tion and food service activities	J – Informa-tion and communic-ation	TOTAL - All sectors	BES - Business enterprise sector
UKM2 - Eastern Scotland	49913	731	5541	8050	1710	1.3	0.7
NL41 - Noord-Brabant	83939	2033	17519	16394	2832	2.4	:
NL21 – Overijssel	31545	596	5603	5502	962	2.1	:
DE25 – Mittelfranken	52321	307	14067	7459	2283	3.5	2.6
AT13 – Wien	69611	33	5921	15777	5577	3.6	1.9
IE02 - Southern and Eastern	125199	1148	26801	20237	12840	1.5	1
EU region median	35909	501	5592	6701	926	1	0.8
Top regions median	51754	345	5762	8910	2557	2.2	1.9
% Difference	44%	-31%	3%	33%	176%	56%	155%
Textile Cluster							
BE25 - Prov. West-Vlaanderen	32939	678	6336	6770	629	1.1	:
BE23 - Prov. Oost-Vlaanderen	38908	385	6831	7448	1083	2.3	:
ES52 - Comunidad Valenciana	93714	2084	13151	22104	2514	1	0.4
NL21 – Overijssel	31545	596	5603	5502	962	2.1	:
ITC4 – Lombardia	310836	2978	62988	60910	17652	1.3	0.9

Table 6 (continued)

	TOTAL - Total - all NACE activities	A – Agricul-ture, forestry and fishing	C – Manufac-turing	G-I - Trade, transport, accommoda-tion and food service activities	J – Informa-tion and communic-ation	TOTAL - All sectors	BES - Business enterprise sector
FR72 - Auvergne	29962	725	4574	4757	514	2.2	1.7
UKD3 - Greater Manchester	62013	37	6097	12786	2835	0.9	0.4
PT11 – Norte	44729	735	8861	9429	1045	1.5	0.7
DED1 - Chemnitz	29874	253	7142	4599	673	1.8	1
FR23 - Haute-Normandie	44132	873	8474	7812	679	1.3	1.1
EU region median	35909	501	5592	6701	926	1	0.8
Top regions median	41520	701	6986	7630	1004	1.4	0.9
% Difference	16%	40%	25%	14%	8%	-3%	14%
Chemical Cluster							
BE32 - Prov. Hainaut	25487	235	3814	4703	614	1.5	:
DEB3 - Rheinhessen-Pfalz	55089	765	16474	7291	2485	3	2.2
UKC1 - Tees Valley and Durham	22085	132	3797	3920	662	0.9	0.5
DEE0 - Sachsen-Anhalt	46208	877	9360	6961	871	1.5	0.4
NL33 - Zuid-Holland	123095	2611	10782	26102	6124	1.9	0.9
NL13 – Drenthe	11711	378	1674	1964	180	0.8	:

Table 6 (continued)

	TOTAL - Total - all NACE activities	**A – Agricul-ture, forestry and fishing**	**C – Manufac-turing**	**G-I - Trade, transport, accommoda-tion and food service activities**	**J – Informa-tion and communic-ation**	**TOTAL - All sectors**	**BES - Business enterprise sector**
NL42 - Limburg (NL)	31169	919	5606	5979	920	2	:
DED3 - Leipzig	21716	192	2661	3417	1424	2.1	0.4
DEA1 – Düsseldorf	162294	508	30101	29112	8080	1.8	1.4
NL31 – Utrecht	50277	257	3384	8995	4522	2	:
EU region median	35909	501	5592	6701	926	1	0.8
Top regions median	38688	443	4710	6470	1172	1.9	0.7
% Difference	8%	-11%	-16%	-3%	27%	32%	-5%
	GOV – Govern-ment sector	**HES - Higher educa-tion sector**	**TOTAL - Total - all NACE activities**	**A – Agricul-ture, forestry and fishing**	**C – Manufac-turing**	**G-I - Trade, transport, accommoda-tion and food service activities**	**J – Informa-tion and communic-ation**
Motor & Electronics Cluster							
DEA5 – Arnsberg	0.1	0.5	16882	132	3391	1896	553
DE72 – Gießen	0.1	0.9	5577	59	850	365	71
DEC0 – Saarland	0.4	0.5	5652	19	1898	469	128
DEA2 – Köln	0.9	0.8	24277	133	3164	2415	1740
DE12 – Karlsruhe	0.8	0.8	18754	99	3791	1606	1262

Table 6 (continued)

	GOV – Govern-ment sector	HES - Higher educa-tion sector	TOTAL - Total - all NACE activities	A – Agricul-ture, forestry and fishing	C – Manufac-turing	G-I - Trade, transport, accommoda-tion and food service activities	J – Informa-tion and communic-ation
DE25 – Mittelfranken	0.3	0.6	13930	166	2213	1082	807
DEA1 – Düsseldorf	0.1	0.3	26971	201	4050	3189	1566
DED1 - Chemnitz	0.2	0.6	6981	126	1516	752	106
DE11 – Stuttgart	0.2	0.2	33549	247	11697	2278	801
FR10 - Île de France	0.4	0.5	133805	197	9392	11604	15550
EU region median	0.1	0.4	8202	180	995	938	209
Top regions median	0.3	0.6	17818	132	3278	1751	804
% Difference	133%	45%	117%	-27%	229%	87%	285%
Wood & Metal Cluster							
SE33 - Övre Norrland	0.2	1.7	4425	125	502	884	189
AT34 – Vorarlberg	0.1	0.1	2658	44	619	369	29
ITH1 – Bolzano/ Bozen	0.1	0.1	5093	419	494	899	127
SE21 - Småland med öarna	0	0.2	5615	311	945	842	124
ES21 - País Vasco	0.1	0.4	:	:	:	:	:
DEA5 – Arnsberg	0.1	0.5	16882	132	3391	1896	553
BE25 - Prov. West-Vlaanderen	:	:	9901	231	1289	1511	166

Table 6 (continued)

	GOV – Govern-ment sector	HES - Higher educa-tion sector	TOTAL - Total - all NACE activities	A – Agricul-ture, forestry and fishing	C – Manufac-turing	G-I - Trade, transport, accommoda-tion and food service activities	J – Informa-tion and communic-ation
AT21 – Kärnten	0.1	0.3	3381	169	547	539	55
ITE2 - Umbria	0.1	0.6	4984	117	747	816	94
FR21 - Champagne-Ardenne	0	0.2	8030	978	1340	613	95
EU region median	0.1	0.4	8202	180	995	938	209
Top regions median	0.1	0.3	5093	169	747	842	124
% Difference	-42%	-32%	-38%	-6%	-25%	-10%	-41%
Computer Cluster							
UKJ2 - Surrey, East and West Sussex	0.2	0.2	10709	95	856	2012	530
UKJ3 - Hampshire and Isle of Wight	0.5	0.3	10807	85	660	1749	820
UKH3 – Essex	0	0.1	5797	86	600	712	208
DE23 – Oberpfalz	:	0.4	8537	219	2078	590	186
UKM2 - Eastern Scotland	0.3	0.2	10600	165	545	1258	344
NL41 - Noord-Brabant	:	:	18573	1082	2928	1548	354
NL21 – Overijssel	:	:	6916	397	785	599	185
DE25 – Mittelfranken	0.3	0.6	13930	166	2213	1082	807
AT13 – Wien	0.3	1.4	16858	8	1554	2011	970

Table 6 (continued)

	GOV – Govern-ment sector	HES - Higher educa-tion sector	TOTAL - Total - all NACE activities	A – Agricul-ture, forestry and fishing	C – Manufac-turing	G-I - Trade, transport, accommoda-tion and food service activities	J – Informa-tion and communic-ation
IE02 - Southern and Eastern	0.1	0.4	24675	347	3642	6946	3126
EU region median	0.1	0.4	8202	180	995	938	209
Top regions median	0.3	0.3	10758	166	1205	1403	442
% Difference	150%	-9%	31%	-8%	21%	50%	112%
Textile Cluster							
BE25 - Prov. West-Vlaanderen	:	:	9901	231	1289	1511	166
BE23 - Prov. Oost-Vlaanderen	:	:	10681	131	1190	1540	288
ES52 - Comunidad Valenciana	0.1	0.5	:	:	:	:	:
NL21 – Overijssel	:	:	6916	397	785	599	185
ITC4 – Lombardia	0.1	0.2	66240	2018	14670	10734	5804
FR72 - Auvergne	0.2	0.4	7586	241	1148	558	139
UKD3 - Greater Manchester	0	0.5	9357	15	492	2175	614
PT11 – Norte	0.1	0.6	10435	231	:	1363	604
DED1 - Chemnitz	0.2	0.6	6981	126	1516	752	106
FR23 - Haute-Normandie	0	0.2	10751	291	2126	916	184
EU region median	0.1	0.4	8202	180	995	938	209

Table 6 (continued)

	GOV – Govern-ment sector	HES - Higher educa-tion sector	TOTAL - Total - all NACE activities	A – Agricul-ture, forestry and fishing	C – Manufac-turing	G-I - Trade, transport, accommoda-tion and food service activities	J – Informa-tion and communic-ation
Top regions median	0.1	0.5	9901	231	1240	1363	185
% Difference	-25%	29%	21%	28%	25%	45%	-11%
Chemical Cluster							
BE32 - Prov. Hainaut	:	:	5952	77	884	893	270
DEB3 - Rheinhessen-Pfalz	0.3	0.2	12564	270	2914	1061	449
UKC1 - Tees Valley and Durham	0	0.3	3630	55	289	287	218
DEE0 - Sachsen-Anhalt	0.6	0.5	10891	408	1800	1867	232
NL33 - Zuid-Holland	:	:	30245	564	2020	4190	760
NL13 – Drenthe	:	:	2619	155	248	194	28
NL42 - Limburg (NL)	:	:	6320	485	935	654	94
DED3 - Leipzig	0.9	0.8	5060	98	550	608	216
DEA1 – Düsseldorf	0.1	0.3	26971	201	4050	3189	1566
NL31 – Utrecht	:	:	11504	149	391	1597	670
EU region median	0.1	0.4	8202	180	995	938	209
Top regions median	0.3	0.3	8605	178	909	977	251
% Difference	142%	-13%	5%	-1%	-9%	4%	20%

of activity which, as time passes, rely less on knowledge-creation and more on standardised production patterns.

In the top computer cluster regions, we observe high levels of GVA and GFCF in the information and communication and the trade, transport, accommodation and food service activities sectors, and low levels of the same metrics in agriculture. The textile cluster regions appear to have higher GVA and GFCF in agriculture, while the regions with high chemical cluster indicator scores do not have median values which vary significantly from the EU regional median, with the most noteworthy differences being observed in information and communication.

Industry Characteristics

In this section, we take a closer look at the sector characteristics of the top-scoring regions based on our cluster indicators. Specifically, we examine descriptive statistics concerning wages, number of employees, number of firms, and firm size.

A first observation (Table 7) that can be made is that regions with the highest scores in motor and electronics, computer and chemicals, tend to have wages that are significantly (≥ 20%) above the EU median in manufacturing, as well as in each sector which is included in their composition. On the other hand, the top regions in wood and metal and textile clustering appear to have manufacturing wages around the EU median and — with the exception of the wood sector — this is also the case with each sub-sector.

A second observation is that these regions, apart from scoring high in regard to relative concentration, also tend to have a high number of employees in each relevant sector. Kemeny and Storper (2015) pointed towards different productivity dynamics underlying absolute and relative types of specialisation. In the case of the former, they argue, the three main mechanisms that increase productivity are 'sharing of input suppliers; matching of specialised labour demand and labour supply […] and technological learning or spillovers' (p. 1006). When it comes to relative concentration, the authors underlined the potential dominant role of an agglomeration in regional demand for resources, as well as in commanding political attention. One can expect, based on the aforementioned dichotomy, that our indicators capture the presence of dynamics connected both to relative and absolute specialisation.

Our findings indicate that the regions where the highest cluster indicator scores are observed tend also to have a higher firm size in the sectors related to each cluster (as indicated by the total regional sector employment divided by the number of units/firms per regional sector). The greatest differences between top cluster and EU median values are observed in the cases of motor vehicles manufacturing (+61%) and chemicals (+56%), while the lowest is in fabricated metal (+10%). The two regions that stand out in regard to size in the motor sector are Ile de France (home of PSA Peugeot Citroën) and Stuttgart (home of Mercedes-Benz and Porsche). In computer equipment, manufacturing the Southern and Eastern Ireland region has by far the largest firm size average — more than twice the size of the second-best region — as is the case with the Rheinhessen-Pfalz region in chemical manufacturing.

A positive effect of firm size on wages has been consistently observed in related literature, including in studies of the European manufacturing sector (Lallemand

Table 7 Top 10 regions' wages, employees, firms, and firm size

Motor & Electronics Cluster

	Wages			**Employees**			**Firms**		**Firm Size**	
	manuf.	motor	electrical	manuf.	motor	Electrical	electrical	motor	electrical	motor
DEA5 – Arnsberg	38589	37580	40540	344081	24097	32045	627	308	51	78
DE72 – Gießen	35345	36790	34780	93216	2756	8853	238	78	37	35
DEC0 – Saarland	37908	43120	34730	97680	18607	2450	105	105	23	177
DEA2 – Köln	41443	51130	40520	260804	32154	16960	464	194	37	166
DE12 – Karlsruhe	41663	45320	44470	290294	45597	32786	495	350	66	130
DE25 - Mittelfranken	40536	41880	49470	195304	10920	23328	334	121	70	90
DEA1 – Düsseldorf	42431	44060	41990	353417	19045	17388	524	319	33	60
DED4 – Chemnitz	22472	33580	25250	139060	22202	8571	296	309	29	72
DE11 – Stuttgart	44289	53760	41030	532190	145162	34982	893	624	39	233
FR10 - Île de France	41960	42860	42640	873542	142423	44128	954	607	46	235
Top-10 cluster regions median	40989	42990	40785	275549	23150	20358	480	309	38	110
EU region median	29446	31820	31980	78338	3269	2912	113	90	27	43
	28%	26%	22%	72%	86%	86%	76%	71%	29%	61%
Wood & Metal Cluster										
	Wages			**Employees**			**Firms**		**Firm size**	

Table 7 (continued)

Motor & Electronics Cluster

	manuf.	wood	fab. metals	manuf	fab. Metals	Wood	wood	fab. metals	wood	fab. metals
SE33 - Övre Norrland	30504	28522	27820	29822	3854	4295	495	638	9	6
AT34 – Vorarlberg	37519	24612	41740	39153	9554	1353	200	302	7	32
ITH1 – Bolzano	25443	17789	24840	31624	4609	5627	1049	406	5	11
SE21 - Småland med öarna	29873	28679	27820	89305	15093	9547	953	1788	10	8
ES21 - País Vasco	30908	19845	28790	194404	44002	4006	745	3759	5	12
DEA5 – Arnsberg	38589	34057	36280	344081	78386	4328	224	3056	19	26
BE25 - Prov. West-Vlaanderen	31839	31524	29640	84228	8584	3575	321	1174	11	7
AT21 – Kärnten	34861	29645	30670	35682	4574	3235	296	367	11	12
ITI2 – Umbria	19855	14170	18090	65254	9408	2957	637	1059	5	9
FR21 - Champagne-Ardenne	30422	26340	30160	67010	13270	3265	293	687	11	19
Top-10 cluster regions median	30706	27431	29215	66132	9481	3791	408	873	9	12
EU region median	29446	22251	28230	78338	9052	2225	263	803	7	10
	4%	19%	3%	-18%	5%	41%	36%	8%	27%	10%

Table 7 (continued)

Motor & Electronics Cluster

Computer Cluster	Wages		Employees		Firms	Firm size	Textile cluster	Wages		Employees		Firms	Firm size
	manuf	computer	manuf	computer	computer	computer		manuf	textiles	manuf	textiles	textiles	textiles
UKJ2 - Surrey, East & West Sussex	30414	31480	80827	10461	488	21	BE25 - Prov. West-Vlaan-deren	31839	27410	84228	11928	482	25
UKJ3 - Hampshire & Isle of Wight	29998	30790	73739	8934	404	22	BE23 - Prov. Oost-Vlaan-deren	36107	26770	82644	6508	244	27
UKH3 - Essex	28975	29480	57226	5750	246	23	ES52 - Comunidad Valenciana	23368	18510	232865	13520	1518	9
DE23 - Oberpfalz	37754	49350	134761	8094	128	63	NL21 - Overi-jssel	36238	34030	64756	3118	176	18
UKM2 - Eastern Scotland	29637	33000	67187	6040	161	38	ITC4 - Lom-bardia	25988	21570	989703	58796	4565	13
NL41 - Noord-Brabant	41302	57650	154801	8759	333	26	FR72 - Auvergne	28861	23240	72147	1631	137	12
NL21 - Overijssel	36238	50160	64756	3487	105	33	UKD3 - Greater Manchester	25313	18970	106706	6809	309	22
DE25 - Mit-telfranken	40536	52260	195304	16619	273	61	PT11 - Norte	10589	10210	356917	37089	2579	14
AT13 - Wien	45185	49530	60735	3200	131	24	DED4 - Chemnitz	22472	19350	139060	6743	317	21
IE02 - Southern and Eastern	41822	51280	114905	12530	91	138	FR23 - Haute-Normandie	31206	19480	67129	1006	92	11
Top-10 cluster regions median	36996	49440	77283	8427	203.5	30	Top-10 cluster regions median	27424	20525	95467	6776	313	16

Table 7 (continued)

Motor & Electronics Cluster													
EU region median	29446	34385	78338	2696	113	22	EU region median	29446	21830	78338	1006	103	8
	20%	30%	-1%	68%	44%	26%		-7%	-6%	18%	85%	67%	49%
Chemical Cluster													
	Wages		**Employees**		**Firms**	**Firm size**							
	manuf	chemicals_w	manuf	chemicals	chemicals	chemicals							
BE32 - Prov. Hainaut	35550	51140	54521	4280	81	53							
DEB3 - Rheinhessen-Pfalz	43260		161263	45702	271	169							
UKC1 - Tees Valley and Durham	31940		48995	6502	87	75							
DEE0 - Sachsen-Anhalt	26830	37340	146859	13301	375	35							
NL33 - Zuid-Holland	39405	62480	109486	9298	161	58							
NL13 - Drenthe	37977	58140	17887	1369	18	76							
NL42 - Limburg (NL)	38296	61500	58656	6369	94	68							
DED5 - Leipzig	28387	39290	46341	1957	93	21							
DEA1 - Düsseldorf	42431	54640	353417	45543	750	61							
NL31 - Utrecht	38022	47390	37263	2450	58	42							
cluster median	37999	52890	56589	6436	94	59							
EU region median	29446	36305	78338	2769	96	26							
	23%	31%	-38%	57%	-3%	56%							

et al., 2007). While this phenomenon has been often linked to productivity differentials, it can arguably also be attributed to other factors underlying large firms' capacity and willingness to offer higher wages (Oi & Idson, 1999). In regard to the debate on the relationship between firm size and innovation-related performance, size advantages of large firms once again come into play, in the form, inter alia, of financial resources, internal knowledge and market power. However, small firms have different types of strengths, such as flexibility and effective communication (Pla-Barber & Alegre, 2007; Rogers, 2004). In a sample similar to the one of the present study, Vaona and Pianta (2008) found that large European manufacturing firms perform better than medium and small sized ones in both product and process innovation. On the other hand, Maskell (2001) argued that the number of firms in a cluster matters for innovation dynamics. For example, the birth of additional new firms and attracting firms from elsewhere is also important for innovative dynamics of a cluster, since co-location of firms within related industries enhances the ability to create knowledge by variation and a deepened division of labour.

Regions with the highest cluster scores do not always have more and bigger firms. The top — scoring regions in the chemical cluster actually have a 3% lower median number of chemical manufacturing firms than the EU total. In the case of the wood and metal cluster, four top regions have a lower median than the EU total median in fabricated metal product manufacturing, and three top regions have a lower median in wood product manufacturing.

Within the same cluster category one can observe a great degree of variance. Düsseldorf has 750 chemicals manufacturing firms, while Drenthe has 18. In the computer manufacturing cluster, the top region (Surrey, East & West Sussex) has an average firm size which is below the EU median (21 employees), and a number of firms which is more than 4 times above the EU median (488). Southern and Eastern Ireland, on the other hand, has an average computer manufacturing firm size of 138 employees — more than 6 times the EU median — and has less firms in the sector than the EU median. In a nutshell, one can observe that in the case of regional innovation systems depicted by our cluster indicator it is not always the case that '(absolute) size matters'.

Discussion

When starting out in this attempt to operationalise the concept of innovation systems by creating a novel cluster indicator, there were many reasons to believe it would lead to a dead end. Maybe patenting activity and manufacturing did not co-locate in a way that would be observable via the methodology applied. Maybe the cluster types identified would resemble existing sectoral taxonomies so closely that our approach would essentially offer no added value. Maybe, on the contrary, by using such an open-ended approach the picture that emerged would be so convoluted that no discernible patterns would be identified.

Yet, what instantly emerged from the data was a picture that corresponded, to a significant extent, to the theoretical foundations on which the methodology was constructed: Certain patterns of co-location of concentrated patenting and manufacturing that were homogeneous enough to be classified into distinct groups, but heterogeneous enough to highlight the need to overcome the confines of narrow sectoral taxonomies when studying innovation dynamics.

What was depicted was the presence, in different occasions, of a local context where patenting and manufacturing activity is co-located in activities that are linked across the value chain. While our methodology does not explicitly account for spillovers and network effects, the assumption, based on the related literature, is that the context depicted tends to provide fertile ground for the development of such dynamics. This has to do with spillovers occurring within regions with a strong concentration of knowledge production and use, but it also relates to the capacity of such regions to attract, absorb and transform external spillovers.

The composition of the cluster groups generated points toward the need to move beyond strict sectoral taxonomies when studying innovation systems, in order to capture the branching to new sectors that may not have been as strongly related previously. Most components produced contained high loadings from three or more different patent categories and it was often the case that they contained loadings from two different employment sector categories. Hence, a priori categorisations, while convenient, fail to capture the complexity of modern knowledge and production eco-systems.

Conclusions

The results of this paper indicate that in today's complex and evolving economy, the study of innovation can benefit from moving past artificial boundaries regarding the nature and structure of innovation systems. In future research, the fundamental principle on which this methodology has been based can be extended and applied to many types of data linked to the innovation process. Given the rapidly growing availability of data and pattern recognition techniques, there is no reason to limit oneself to static assumptions. It is easy to understand why studying the automotive industry without taking into account electronics would not make sense, yet this is exactly what one would do if relying on previously applied taxonomies. A main direction this research can be built upon is by addressing one of its main limitations, namely the absence of explicit modelling of connections between actors in the innovation systems. In the model presented, such connections have been assumed to exist based on collocation in order to be able to apply the methodology on a large scale. However, using data, for instance, on co-citations and input-outputs and methods on network analysis, one can narrow down on specific clusters produced and provide a more complete picture by depicting intra-regional and inter-regional linkages. Furthermore, while the current analysis provides a single 'snapshot' of cluster composition, the same methodology can be applied to data spanning a wider time-frame, in order to depict the evolution of cluster dynamics in more detail. This will potentially allow for the study of ways in which regional clusters follow path-dependent trajectories and also create new paths by branching to related sectors.

This point has direct policy implications, since it is imperative for policy-makers to have a real-time view of the geography of innovative activity. Much can be lost in translation if policy is designed based on models that fail to illustrate emerging and evolving innovation ecosystems. The evolution of an economy is a complex process whose effects have many dimensions. Adapting to it in a way that benefits society the most requires constantly recalibrating our assumptions in accordance with the economy's rapid transformations. This can translate in tailor made policy initiatives that will help build on regional advantages while also generating the potential for diverse evolutionary trajectories.

Data Availability The data sources utilised in this study are the OECD REGPAT database, which includes regionalised EPO patent application data, and the Eurostat Structural Business Statistics database, which includes NUTS 2-level employment data. These datasets are publicly available. Access to the OECD REGPAT database can be obtained through the OECD's official website (https://www.oecd.org/sti/inno/intellectual-property-statistics-and-analysis.htm#ip-data), while the Eurostat Structural Business Statistics can be accessed via the Eurostat data portal (https://ec.europa.eu/eurostat/web/structural-business-statistics/database). We have ensured transparency and reproducibility by using publicly accessible datasets, allowing other researchers to verify and build upon our findings.

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