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Abstract

This paper introduces a new approach for the definition of innovation clusters, based on the co-location of concentrated patenting and manufacturing activity in the EU. The incorporation of data on both the production and use of technologies results in an indicator that depicts both formal and informal modes of innovation and conditions which can be expected to be conducive to the generation, diffusion and absorption of innovation, and consequently the enhancement of competitiveness. Our findings indicate that certain types of patenting and manufacturing activity tend to co-locate. The sectoral-technological composition of the three types of concentrations observed points towards a higher level of diversity than one would expect in the case of narrow specialisation. Applying the new indicator in a test of the often hypothesised benefits of innovative clustering, we find that the identified clusters have consistently higher wages in the sectors concerned.

JEL Classifications: O30, R12, L60

Keywords: Innovation, clusters, regional studies, patenting, manufacturing

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1 Introduction

The study of innovation occupied a peripheral position in economics literature during the better part of the 20th century. The most notable exception was, arguably, Joseph Schumpeter who placed technological change in the centre of his analysis in order to address the issue of, as he put it, 'how the economic system generates the force which incessantly transforms it' (Schumpeter 1937: 158).

The prevalent narrative in the study of economic growth in the middle of the 20th century was largely influenced by Solow's (1957) 'neoclassical growth theory' which approached technological change as an exogenous factor. This assumption, combined with those regarding the decreasing returns to capital and the nature of technology as a 'public good', led to the expectation of convergence of different economies, given that markets were allowed to function freely. Models that endogenised technology and innovation were developed in the same period (e.g. Kaldor 1957), but it was not until the late 1980's that it began to become broadly apparent that the available empirical evidence failed to constitute a strong case in support of convergence on a large scale (for an overview of the convergence debate: see Islam 2003). This lack of empirical support for convergence initiated a widespread search for new ways to approach the mechanics underlying the process of economic growth, with particular focus being placed on the conceptualisation and assessment of the dynamics and impact of innovation (Fagerberg 1987, Lucas 1988, Romer 1990, Aghion & Howitt 1992).

Incorporating innovation in economic analysis is, of course, far from a straight-forward process, given the fluid nature of the concept. Innovation, as Kline and Rosenberg (1986: 283) point out, is not homogenous and well-defined and it is usually impossible to pin down the specific point in which it enters the economy. By extension, conceptualising the process that leads to innovation also poses a significant challenge. Traditionally, researchers tended to approach it as a 'linear' process, where research leads to inventions which, in turn, pave the way for innovation. This perspective facilitates the implementation of empirical analysis where R&D spending and patents can serve as proxies for the 'input' and 'output' of innovation respectively (MacLaurin 1953). Placing, however, an overly strict focus on this one-dimensional view of the innovation process entails the risk of overlooking the context in which innovation takes place and limiting oneself to a deterministic type of analysis.

2 Literature

2.1 Innovation Systems

The theory of 'innovation systems' which emerged in the 1980's and gradually gained prominence (Freeman 1987, Lundvall 1985, 1992, Edquist 1997, Nelson 1993) sought to study innovation as a multi-faceted, interactive process and to emphasise the role of knowledge and learning as a driver for growth. Lundvall (1992, p. 2) defined the National Innovation System as constituted by 'the elements and relationships which interact in the production, diffusion and use of new, and economically useful, knowledge'. While information can be perceived as being factual (Saviotti 1988), knowledge allows for correlations and syntheses between different types of variables and pieces of information, and therefore generates the potential for the creation of new information (Andersson 1985, Saviotti 1998).

A concept which serves as a foundation for this broad theoretical framework is that of knowledge spillovers, examined by Marshall (1890) in his highly influential study of industrial agglomeration and expanded upon by a number of authors in later decades (Arrow 1962, Jaffe 1986, Glaeser et al. 1992). While Marshall focused on intra-industry spillovers, Jacobs (1969) underlined the role of spillovers between different, complementary industries, establishing what has since been labelled as 'Jacobian diversification externalities'. Knowledge spillovers in general are especially important when it comes to knowledge that is not easily codifiable and therefore not easily transferable through long distances. This un-codified knowledge, which seems to be 'in the air', is what Polanyi (1958) refers to as 'tacit knowledge'.

Assuming that knowledge is often cumulative in nature (Nelson and Winter 1982), one can expect a certain degree of path dependency in technological change. The nature of path dependencies that affect firm, regional or national economic performance is rarely strictly economic, but often extends to institutions and policies (North 1990, Pierson 2000) and various authors have underlined the role of the institutional and historical context in defining future innovation patterns (Arthur 1994, David 1985). A situation in which an economic system, as a result of path dependency, is trapped in a modus operandi which does not allow it to achieve superior outcomes is labelled a 'lock-in by historical events' by Arthur (1989). In the study of technological change, path dependency is often incorporated within the concept of the 'technological paradigm' (Dosi 1982).

Most of the early work that can be viewed as belonging to the innovation systems framework focused on the national level. However, since the mid-1990's the study of regional innovation systems (RIS), broadly defined as 'interacting knowledge generation and exploitation subsystems linked to global, national and other regional systems' (Cooke 2004: 3), gained traction and the region has since been increasingly viewed as the key level at which innovation capacity is fostered (Asheim et al. 2005, Braczyk et al. 1998, Carlsson 2004, Cooke 1997, 2004, Doloreux and Parto 2005). Regional capabilities, Maskell and Malberg (1995:27) argue, emanate not only from human and natural resources but also from the knowledge that is embedded in the region's industrial and institutional structure and are therefore often hard to imitate, hence potentially generating durable competitive advantages. Apart from RIS, a number of very similar conceptual frameworks that study the regional context and dynamics of innovation have emerged, including 'learning regions' (Morgan 1997), 'innovative milieux' (Aydalot and Keeble 1988, Maillat 1998), and 'clusters' (Porter 1990), and these terms have often being used interchangeably in the related literature.

As Edquist (1997, p. 3-15) pointed out, the National Innovation Systems' concept is part of a larger family of 'systems of innovation' approaches, which differ in regards to their object and level of analysis (supranational, regional, sectoral or technological systems of innovation, clusters). An important insight of the sectoral systems approach (Malerba 2002) is that it is not only geographical proximity that matters, but also the proximity between sectors and their sector specific innovation processes, institutions and resources. Malerba (2002) labelled this concept 'sectoral systems of innovation and production', which he defined as: 'a set of products and the set of agents carrying out market and non-market inter-actions for the creation, production and sale of those products' (Malerba 2002, p. 247).

At the policy level, adopting aspects of this viewpoint translates into an attempt to complement traditional strategies for pursuing growth with a search for ways to strengthen the linkages between the actors (or sub-systems) of a (regional and/or sectoral) innovation system. Most notably, between technology producing and technology using actors (or sub-systems).

As the study of innovation has rapidly grown in popularity in recent years, the aforementioned approaches have contributed extensively and multi-angularly to the understanding of innovation and its links to economic growth. There has, however, been limited cross-fertilisation of different theoretical strands when it comes to the development of theoretical mechanisms. According to Crescenzi and Rodríguez-Pose (2011) this can be attributed to the 'different disciplinary backgrounds of the researchers working on innovation, to the different methods used by different approaches, and to the difficulties in operationalising some of the concepts used by different strands of the literature on the topic' (2011: 10).

2.2 Clusters

Porter's (1990, 1998, 2000) seminal work on clusters has been widely influential in recent years when it comes to examining the ways in which firms' co-location and linkages can serve as a foundation for the development of competitive advantages. Porter (2000: 254) defines a cluster as 'a geographically proximate group of inter-connected companies and associated institutions in a particular field, linked by commonalities and complementarities'.

Firms and associated organisations like academic and local government institutions can operate more efficiently within a regional cluster, Delgado et al. (2012) argue, since they share access to a common pool of knowledge, technology, infrastructure and supply and demand.

It is important to emphasise that Porter identifies specialisation in clusters of related industries as a potential driver for higher regional performance. It follows that diversification within a region is not necessarily beneficial per se when it comes to the process of localised learning, since a certain degree of cognitive proximity is required in order for knowledge spillovers to take place. Too much cognitive proximity on the other hand, however, can lead, Nooteboom (2000) notes, to cognitive lock-in. The concept of related variety (Frenken et al. 2007), refers to the point of balance between cognitive distance and cognitive proximity, where knowledge spillovers can be expected to have a maximum effect on regional economic growth.

The majority of empirical work on clusters is based on case studies, as one would expect, given the idiosyncratic nature of economic systems and the socio-historic context in which they are located. Even within a very narrow case study analysis it is impossible to account for the numerous complementarities and interlinkages within a cluster, let alone intangible factors such as local 'buzz' (Storper and Venables 2002). Past qualitative studies have been particularly focused on Third Italy (Sforzi 1989), Baden-Württemberg (Fuchs and Wassermann 2005) and Silicon Valley (Saxenian 1996).

The number of studies that attempt to quantitatively operationalise clusters on a large scale is very limited. Notable examples include work by Feldman and Audretsch (1999) on science-based clusters, Feser and Bergman (2000) who define clusters in terms of inputs and outputs and Porter (2003), whose methodology was expanded upon by Delgado et al. (2014) and used in the US Cluster Mapping Project. In the European Union the European Cluster Observatory has mapped employment clusters at the regional level (European Commission 2007).

This paper aims to introduce a new way of depicting clusters, on the basis of the co-location of concentrations of patenting activity and manufacturing employment at the EU NUTS II level. High values of the cluster indicators 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.

3 A New Way of Defining Clusters

The point of departure for the following analysis is the conceptual definition of clusters as geographically concentrated systems of economic and innovation activity in related sectors.

The first phase, in the attempt to quantitatively operationalise EU clusters at the NUTS 2 level, consists of the construction of location quotients using data on (mainly) manufacturing employment and patent applications in different sectors, in order to depict concentrations in economic and innovation activity respectively. Or, to put it differently: Indicators that respectively capture concentrations in technology using and technology producing activity.

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 Commission 2007, European Cluster Observatory 2014a). The widespread use of this type of methodologies by researchers in related fields is facilitated by the relatively easy access to employment data. It is worth noting that the European Cluster Observatory uses wages as an indicator for cluster strength (European Cluster Observatory 2014b). Our hypothesis is that our co-located systemic approach of the production and use of technology captures this higher wage dynamism and we proceed to test this hypothesis in section 4.3.

The present analysis will seek to combine location quotients for employment (mainly in manufacturing) with the introduction of patent location quotients.

Manufacturing Employment LQ:

$$\frac{Manufacturing\ subsector^{3}\ regional\ employment}{Manufacturing\ total\ regional\ employment} \Bigg/ \frac{Manufacturing\ subsector\ EU\ employment}{Manufacturing\ total\ EU\ employment}$$

Patent LQ:

$$\frac{IPC^{4}\ class\ regional\ patents}{total\ regional\ patents} \Bigg/ \frac{IPC\ class\ EU\ patents}{total\ EU\ patents}$$

An indicator based on detailed patent application data provides a region and sector-specific proxy for both R&D output and innovation input. It can add a dimension of analysis connected to what is referred to in evolutionary economic geography literature as the cognitive foundations of regional innovation systems.

Patents are the most popular indicator used as a proxy for what can be broadly defined as innovative activity. Apart from the obvious direct conceptual linkage between patenting and innovation, the popularity of the use of patent data can also be attributed to their high level of availability and detail.

The use of patents as an indicator for innovative activity, however, is not without its shortcomings. One potential disadvantage of the use of patents has to do with the inability to assess the economic value of each patent. While a patent indicates the presence of an invention, there is no indication regarding whether or not this invention was commercialised. A study by Feldman (1994) found that there was a significant correlation between the location of patents and new products introduced to the market. These findings are, nevertheless, far from conclusive (Feldman and Kogler 2010). Other problems

[3] Based on the Statistical Classification of Economic Activities NACE, Rev.1.1 of the European Union
[4] International Patent Classification. Detailed descriptions of IPC classes are available at http://web2.wipo.int/ipcpub

connected to the use of patents as an innovation proxy have to do with differences in the propensity of patenting among industries (Cohen et al. 2000). For a detailed overview of the strengths and weaknesses of the use of patents as economic and innovation indicators, see Basberg (1987) and Griliches (1990).

Patent data offer useful information regarding a particular type of innovation which has been labelled by Jensen et al. (2004) as Science-Technology-Innovation (STI). This term refers to a more 'formal' mode of innovation which is based on R&D and whose 'output' can often be captured 'explicitly', in terms of scientific publications, patent applications, etc. However, focusing only on STI would present a very narrow depiction of the innovation process.

Jensen et al. (2004) refer to a mode of innovation they label Doing-Using-Interaction (DUI) which represents a more 'informal' process based on learning that involves types of knowledge which, in contrast to STI, cannot be easily codified. This 'tacit' kind of knowledge we referred to in the previous section, is often fostered on the job and enhanced through relationships between employees.

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 breeding ground for interactive learning (Lundvall 1985, 1992, 2010; Asheim 2001), where codified knowledge can be used in the production process and 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 (Karlsen et al. 2011, Isaksen and Nilsson 2011).

In order to portray the presence of regional characteristics related to DUI, we constructed LQs for employment in a set of manufacturing sectors. Manufacturing is commonly perceived as the economic sector with the most significant impact on growth, due to, inter alia: higher productivity, greater capacity for the generation of capital accumulation, innovation and spillover effects (Cornwall 1977).

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 (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 taken into account was that of the inventor, since it gives information about innovation activity in the specific region, contrary to the applicant's address which refers to the location of the company that owns the patent and 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.

Employment LQs for 10 manufacturing sectors and one for construction were formulated using data provided by Eurostat[5].

Having created a database containing 193 regions[6] with 11 categories of employment LQs for 2000 and 118 categories of LQs corresponding to IPC classes for the one-year average of 1999-2001 EPO patents, the next goal was to bring the variables down to a more manageable number and then proceed to study their co-location. In order to achieve this, a Principal Component Analysis (henceforth PCA) was implemented.

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 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).

The 69 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. Out of these 69 regions, 28 had less than 20 total patents and 16 had less than 10.

[5] Eurostat databases used: Structural Business Statistics (sbs_r_nuts03) and European Union Labour Force Survey (lfst_r_lfe2en1)
[6] Luxemburg, Denmark, UKM5, UKM6, ES63, ES64, PT20, PT30 were excluded due to a lack of employment data, while France's overseas regions (FR91, FR92, FR93, FR94) were also not included.

The locations quotients were initially standardised using z-scores. The first stage consisted of a set of PCAs implemented separately at every IPC section[7] in order to reduce the number of variables. This led to the creation of 49 factors. A second-stage PCA was then implemented introducing the employment LQs alongside the factors generated in the first step.

This method attempts to introduce a more holistic approach of depicting innovation clusters by constructing composite indicators which incorporate elements of the traditional employment-focused cluster studies in order to move beyond the strict focus on patents which, as has already been mentioned, entails the risk of painting a picture of innovation which has little value regarding actual economic impact. The cross-sectional implementation of the PCA allows for the examination of the co-location of different types of patenting and manufacturing activities.

4 Results

4.1 Clusters of technology production and use: Three types of cross-sectoral combinations

The three principal components extracted from the second-stage PCA, which depict the cross-sector clustering of patent and manufacturing activity, are presented in Table 1 in the form of the rotated component matrix. We observe three major patterns in the production and use of technologies in industrial production.

The relative importance of each type of activity within the broader components is depicted by the factor loadings. For interpretation purposes we have made a choice of factors applying a cut-off rate of 0.3 for the positive loadings of employment LQs and 0.4 for the loadings of patent LQs[8].

[7] The detailed composition of the IPC classes is available at the website of the World Intellectual Property Organization: http://www.wipo.int/classifications/ipc/en/

[8] In the one case of a variable having a factor loading above the cut-off point on two components we choose to assign it to the component on which it has the higher loading. In the one case where a variable loads above 0.2 on all 3 components we choose to not assign it to a single component.

Table 1: Cross-sectoral PCA Rotated Component Matrix

	Component		
	1	2	3
Employment			
Food products, beverages and tobacco Manufacturing (DA)	-.107	-.351	-.002
Textiles and textile products Manufacturing (DB)	.221	-.221	.313
Wood Manufacturing (DD)	.677	-.177	-.125
Pulp, paper, publishing, printing Manufacturing (DE)	-.242	-.415	-.366
Chemical products and man-made fibres Manufacturing (DG)	-.551	-.232	.128
Rubber and Plastic Manufacturing (DH)	-.019	.162	.321
Metals Manufacturing (DJ)	.458	-.014	.161
Machinery Manufacturing (DK)	.230	.498	.048
Electrical Equipment Manufacturing (DL)	-.298	.321	-.596
Transport Equipment Manufacturing (DM)	-.189	.598	.091
Construction Employment (F45)	.278	-.181	-.019
Patenting			
Human Necessities (A) Factor 1	.274	.055	.061
Human Necessities (A) Factor 2	.104	-.373	.242
Human Necessities (A) Factor 3	.467	.085	.069
Human Necessities (A) Factor 4	-.018	-.093	-.003
Human Necessities (A) Factor 5	-.061	.136	-.002
Performing Operations and Transporting (B) Factor 1	.067	-.066	.441
Performing Operations and Transporting (B) Factor 2	.354	-.117	.103
Performing Operations and Transporting (B) Factor 3	.514	.046	.118
Performing Operations and Transporting (B) Factor 4	.140	.435	.321
Performing Operations and Transporting (B) Factor 5	.307	.153	-.059
Performing Operations and Transporting (B) Factor 6	-.008	.349	-.012
Performing Operations and Transporting (B) Factor 7	.149	.068	-.043
Performing Operations and Transporting (B) Factor 8	.062	.080	.161
Performing Operations and Transporting (B) Factor 9	-.075	.098	.099
Performing Operations and Transporting (B) Factor 10	.159	-.323	.148
Performing Operations and Transporting (B) Factor 11	.118	.321	.005
Performing Operations and Transporting (B) Factor 12	.247	-.020	-.346
Performing Operations and Transporting (B) Factor 13	.037	.212	-.160
Performing Operations and Transporting (B) Factor 14	-.081	.042	.219
Chemistry and Metallurgy (C) Factor 1	-.013	.125	.104
Chemistry and Metallurgy (C) Factor 2	.553	-.106	-.068
Chemistry and Metallurgy (C) Factor 3	-.265	-.191	.389
Chemistry and Metallurgy (C) Factor 4	.009	-.263	-.102
Chemistry and Metallurgy (C) Factor 5	-.093	.028	.486
Chemistry and Metallurgy (C) Factor 6	-.157	.253	-.014
Chemistry and Metallurgy (C) Factor 7	.438	.424	.047
Chemistry and Metallurgy (C) Factor 8	-.050	-.017	.091
Chemistry and Metallurgy (C) Factor 9	.180	-.025	.320
Textiles and Papers (D) Factor 1	.137	-.118	.218
Textiles and Papers (D) Factor 2	-.146	.176	.510
Textiles and Papers (D) Factor 3	.186	-.032	.325
Fixed Constructions (E) Factor 1	.382	.225	.414
Fixed Constructions (E) Factor 2	.450	.038	.085

Fixed Constructions (E) Factor 3	.297	-.103	-.147
Mechanical Engineering etc.(F) Factor 1	.397	.187	.152
Mechanical Engineering etc.(F) Factor 2	.028	.621	.136
Mechanical Engineering etc.(F) Factor 3	.499	.009	.042
Mechanical Engineering etc.(F) Factor 4	.178	.111	.326
Mechanical Engineering etc.(F) Factor 5	.215	.261	-.134
Mechanical Engineering etc.(F) Factor 6	.101	.118	-.150
Mechanical Engineering etc.(F) Factor 7	-.192	-.008	-.076
Physics (G) Factor 1	-.110	.012	-.478
Physics (G) Factor 2	-.176	.349	-.401
Physics (G) Factor 3	.046	.193	-.116
Physics (G) Factor 4	-.086	.451	.093
Physics (G) Factor 5	-.220	-.251	-.017
Physics (G) Factor 6	.147	.276	.020
Electronics (H) Factor 1	-.153	-.027	-.570
Electronics (H) Factor 2	.154	.567	-.155

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization

The main 'ingredients' of these three components, or cluster types, are presented in the following tables. In accordance to the employment and patent sectors of which they are composed, they have been labelled 'Metal, Wood and Construction', 'Machinery', and 'Chemicals and Textiles'.

As is the de facto case in PCA analysis, the precise choice of labelling is based on the authors' subjective interpretation of factor loading patterns. E.g. when assigning a name to the first cluster we included 'construction' although the factor loading for the construction sector is not that high relative to the metal and wood sectors (Table 1). Our interpretation, however, was that it conceptually captures the combination of technologies and applications involved (Table 2).

It is also worth taking a look at the negative factor loadings and observing, for instance, that regions that score highly in regards to the clustering type we named 'Chemicals and Textiles' tend to perform poorly when it comes to electronics patenting, as demonstrated by the negative factor loadings of the two electronics patenting factors on the third component (Table 1).

Table 2: Composition of 'Metal, Wood and Construction' clusters

Employment:

DD MANUFACTURE OF WOOD AND WOOD PRODUCTS

DJ MANUFACTURE OF BASIC METALS AND FABRICATED METALS

(F45 CONSTRUCTION)[9]

Patents:

A factor 3: A45 HAND OR TRAVELLING ARTICLES | A47 FURNITURE; DOMESTIC ARTICLES OR APPLIANCES ETC

B factor 3: B21 MECHANICAL METAL-WORKING WITHOUT ESSENTIALLY REMOVING MATERIAL; PUNCHING METAL | B22 CASTING; POWDER METALLURGY | B23 MACHINE TOOLS; METAL-WORKING NOT OTHERWISE PROVIDED FOR | B27 WORKING OR PRESERVING WOOD OR SIMILAR MATERIAL; NAILING OR STAPLING MACHINES IN GENERAL

C factor 2 and 7: C21 METALLURGY OF IRON |C22 METALLURGY; FERROUS OR NON-FERROUS ALLOYS; TREATMENT OF ALLOYS OR NON-FERROUS METALS | C04 CEMENTS; CONCRETE; ARTIFICIAL STONE; CERAMICS; REFRACTORIES | C14 SKINS; HIDES; PELTS; LEATHER

F factor 3: F23 COMBUSTION APPARATUS; COMBUSTION PROCESSES | F27 FURNACES; KILNS; OVENS; RETORTS

E factor 2:E02 HYDRAULIC ENGINEERING; FOUNDATIONS; SOIL-SHIFTING | E03 WATER SUPPLY; SEWERAGE

Merely based on the high factor loading for employment in manufacturing of transport equipment the label given to the second cluster could have been 'automotive', but when we look at all the involved technologies and sectors (Table 3), we think 'Machinery' better fits as the overarching label for this cross-sectoral combination.

Table 3: Composition of 'Machinery' clusters

Employment:

DK MANUFACTURE OF MACHINERY

DM MANUFACTURE OF TRANSPORT EQUIPMENT

DL - MANUFACTURE OF ELECTRICAL AND OPTICAL EQUIPMENT

Patents:

B factor 4: B60 VEHICLES IN GENERAL | B62 LAND VEHICLES FOR TRAVELLING OTHERWISE THAN ON RAILS

F factor 2: F01 MACHINES OR ENGINES IN GENERAL; ENGINE PLANTS IN GENERAL; STEAM ENGINES | F02 COMBUSTION ENGINES; HOT-GAS OR COMBUSTION-PRODUCT ENGINE PLANTS

G factor 4: G05 CONTROLLING; REGULATING | G21 NUCLEAR PHYSICS; NUCLEAR ENGINEERING

H factor 2: H01 BASIC ELECTRIC ELEMENTS | H02 GENERATION, CONVERSION, OR DISTRIBUTION OF ELECTRIC POWER | H05 ELECTRIC TECHNIQUES NOT OTHERWISE PROVIDED FOR

[9] With a 0.278 loading it is marginally below the 0.3 threshold but we include it due to its direct conceptual relevance

The composition of the ‘Chemicals and Textiles’ cluster is based on high loadings for employment in the rubber and plastics sector and in textiles manufacturing (Table 1 and Table 4), in combination with a set of patents categories that include ‘mineral or slag wool’, ‘lubricants’ and ‘fibres’, ‘knitting’ and ‘non-woven fabrics’.

Table 4: Composition of ‘Chemicals and Textiles’ clusters

Employment:

DB MANUFACTURE OF TEXTILES AND TEXTILE PRODUCTS

DH MANUFACTURE OF RUBBER AND PLASTIC PRODUCTS

Patents:

B factor 1: B05 SPRAYING OR ATOMISING IN GENERAL; APPLYING LIQUIDS OR OTHER FLUENT MATERIALS TO SURFACES, IN GENERAL | B32 LAYERED PRODUCTS | B65 CONVEYING; PACKING; STORING; HANDLING THIN OR FILAMENTARY MATERIAL

C03 GLASS; MINERAL OR SLAG WOOL | C10 PETROLEUM, GAS OR COKE INDUSTRIES; TECHNICAL GASES CONTAINING CARBON MONOXIDE; FUELS; LUBRICANTS; PEAT

D factor 2: D01 NATURAL OR MAN-MADE THREADS OR FIBRES; SPINNING | D04 BRAIDING; LACE-MAKING; KNITTING; TRIMMINGS; NON-WOVEN FABRICS

Taking a look at Table 5, it is interesting to note that most of the top-scoring regions in every cluster indicator have a long history in the industries concerned or related sectors. This observation is in line with the literature concerning path dependency in innovation systems (Fagerberg et al 2008, Martin and Sunley 2006) and in this respect the three identified patterns of clustering can also be interpreted as three main trajectories of industrialisation. There is, of course, quite some degree of diversity within in each cluster type, since not every region performs equally high in every area of activity included.

In the case of the ‘Chemicals and Textiles’, for instance, Lancashire (UKD4) –the world’s leading cotton manufacturer in the first quarter of the 19th century- is among the top regions when it comes to concentrated manufacturing employment in textiles. It is also among the highest performing when it comes to rubber and plastic manufacturing employment, as well as in concentrated patenting activity in areas such as ‘glass; mineral and slag wool’ (C03), for example. This arguably reflects the evolution of the region’s industry –pointing towards a process Martin and Simmie (2008) refer to as ‘evolutionary path dependent development’- from a strict focus on traditional textiles to the diversification towards artificial fibres thanks to the great strides achieved in chemistry

(Berlin et al 2015). On the other hand, the place in the top 10 of the region of Auvergne (FR72), the home of Michelin, is to a great extent due to its exceptional performance in activities more narrowly related to rubber and plastic.

Table 5: Top Regional Clusters

'Metal, Wood, Construction'	**'Machinery'**	**'Chemicals and Textiles'**
SE31 - Norra Mellansverige	DE11 - Stuttgart	FR22 - Picardie
ITH4 - Friuli-Venezia Giulia	FR43 - Franche-Comté	BE32 - Prov. Hainaut
ITH3 - Veneto	DE25 - Mittelfranken	UKD4 - Lancashire
SE21 - Småland med öarna	DE91 - Braunschweig	DED4 - Chemnitz
AT34 - Vorarlberg	DE23 - Oberpfalz	DEB3 - Rheinhessen-Pfalz
SE33 - Övre Norrland	DED4 - Chemnitz	FR21 - Champagne-Ardenne
AT31 - Oberösterreich	DE24 - Oberfranken	FR72 - Auvergne
AT22 - Steiermark	DE22 - Niederbayern	DE73 - Kassel
AT33 - Tirol	DE27 - Schwaben	DEC0 - Saarland
ES52 - Comunidad Valenciana	DE21 - Oberbayern	FR23 - Haute-Normandie

4.2 Geographical patterns

We use the component factor scores in order to create maps that demonstrate the extent to which each cluster type is present in each region. It is easily discernible that the scores of our cluster indicators our not distributed evenly. Examining the map for the 'Metal, Wood and Construction' type of cluster (Figure 1) we observe that Ireland, Portugal, southern Italy and Greece form a 'periphery' of low scores.

Figure 1: Map of 'Metal, Wood and Construction' cluster scores

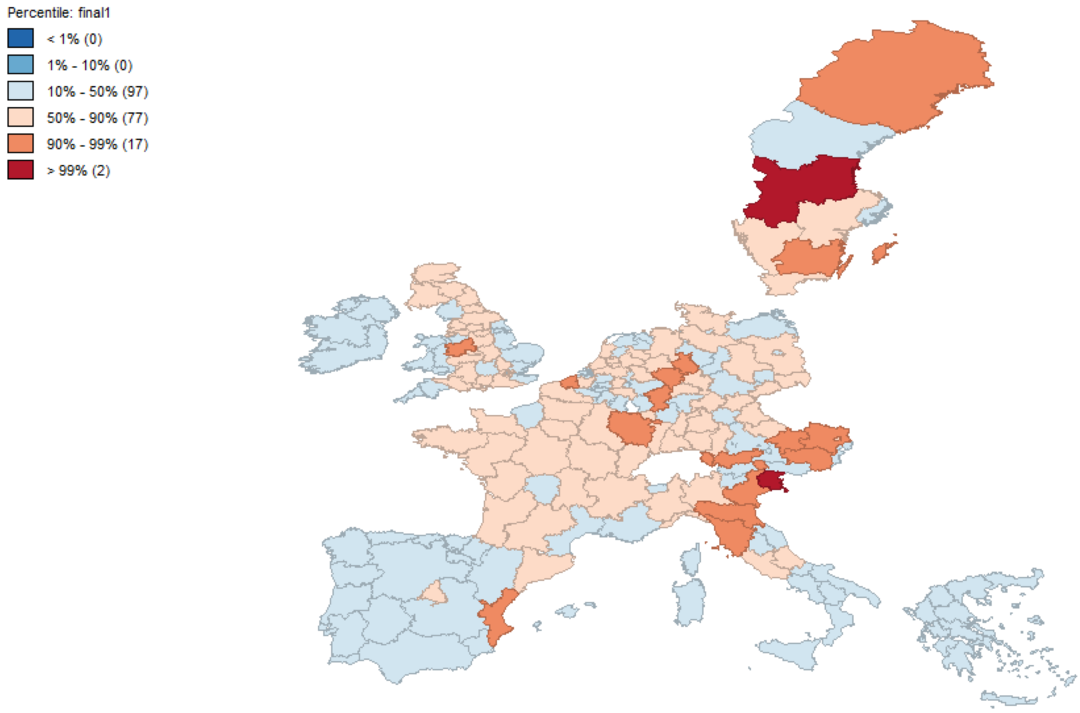
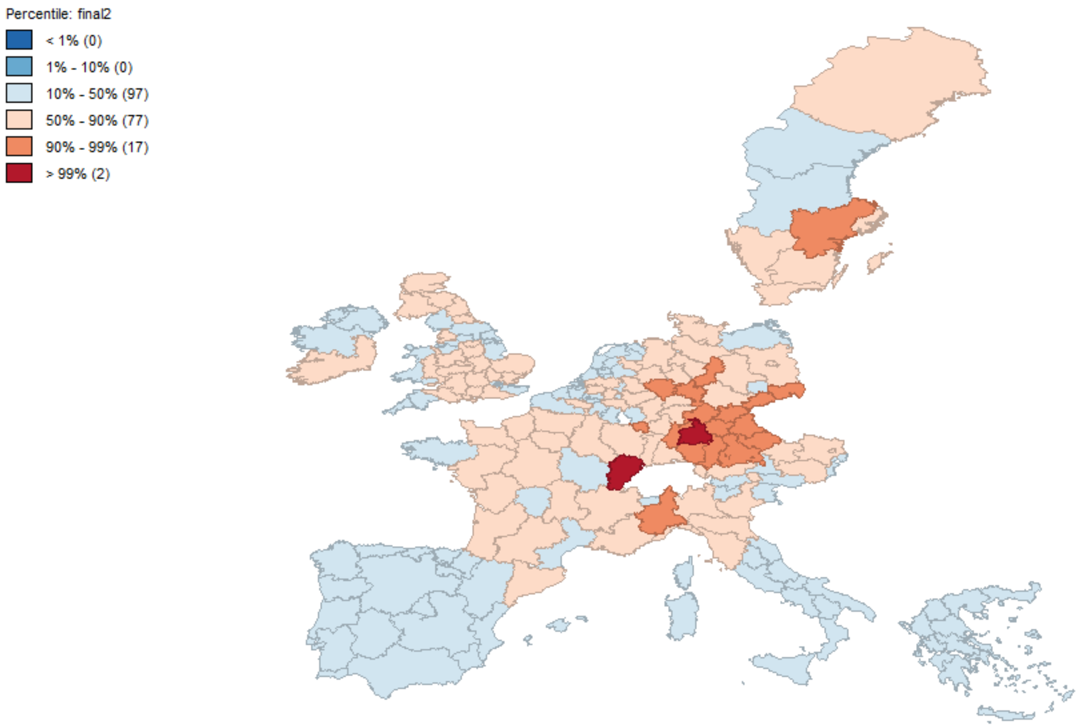


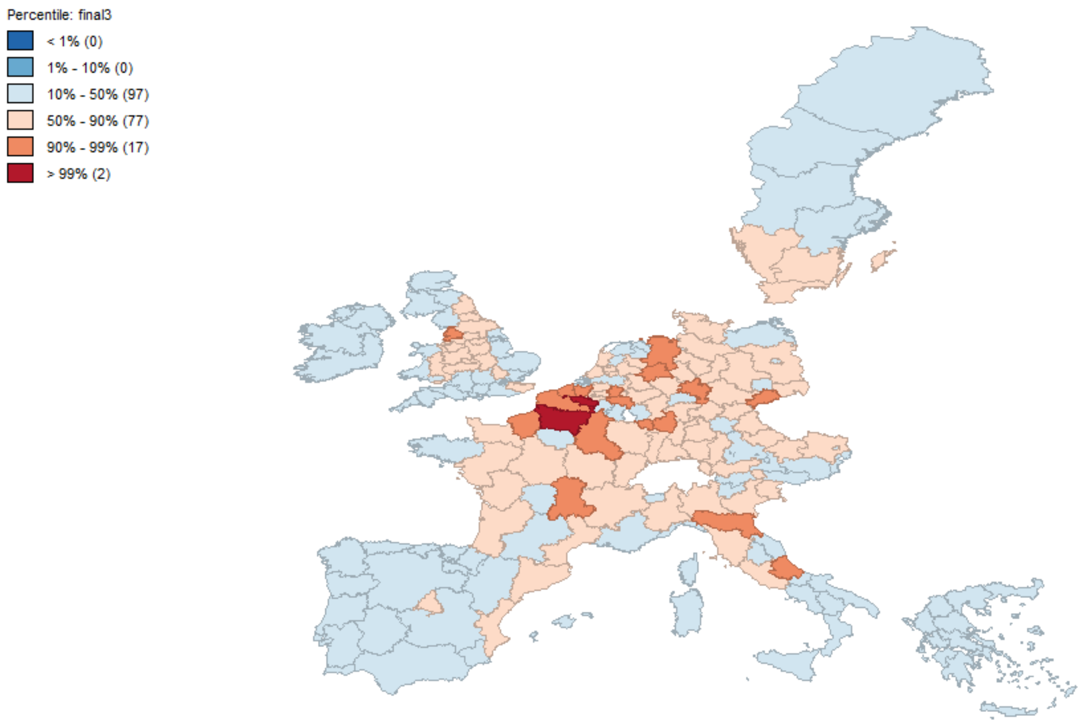
Figure 2: 'Machinery' cluster scores



The geographical pattern of the 'Machinery' cluster indicator shows an even more concentrated picture at the European level (Figure 2), with one clear core in southern Germany.

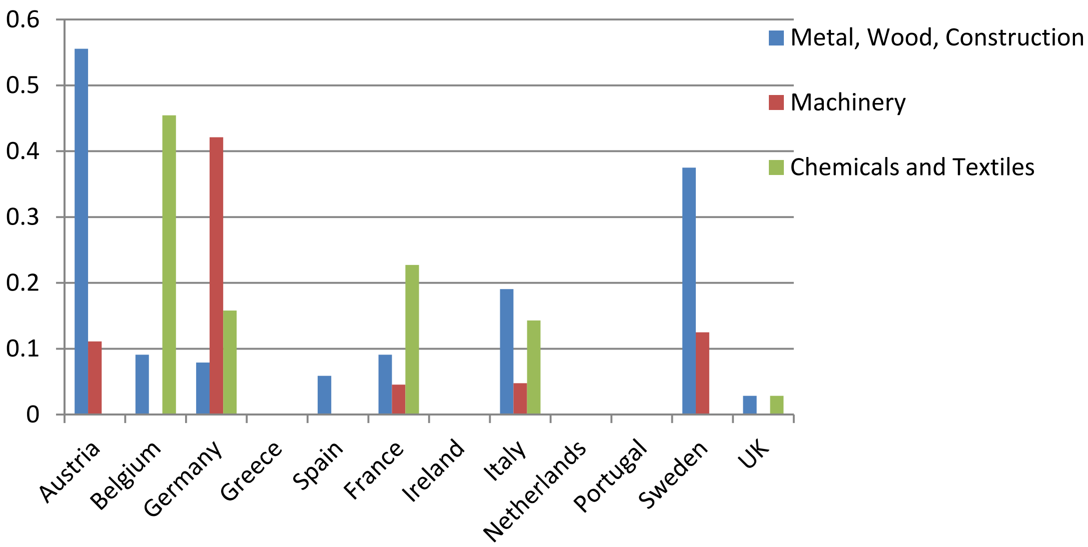
The core of the cluster which we have labelled 'Textiles & chemicals' is in North-west France and Belgium (Figure 3).

Figure 3: 'Chemicals and Textiles' cluster scores



We continue by defining a regional cluster as a region whose cluster indicator value is in the 90th percentile, in order to calculate the number of clusters per region in each country (Figure 4). We observe that Austria has the best performance when it comes to the 'metal, wood and construction' type of innovative clustering, followed by Sweden and Italy. Germany is by far the dominant force in 'Machinery' clustering. Belgium has the higher ratio in 'Chemicals and Textiles' kind of clusters, with France, Germany and Italy following.

Figure 4: Clusters per region, by type of cluster and by country



It is by now apparent that our cluster indicators seem to cluster geographically. The next question we seek to address is to what extent do nearby regions tend to have similar cluster scores.

In order to assess the degree of inter-regional spatial concentration of innovation activity as depicted by the cluster indicators, we study the Moran's coefficient, after having created a first-order queen contiguity weight matrix[10]. Moran's I is a statistic which measures spatial autocorrelation, i.e. the correlation of characteristics of proximal locations, and its values range from -1 (perfect dispersion) to 1 (perfect concentration).

Table 5: Spatial Autocorrelation of Cluster Indicator values

Cluster	Moran's I
'Metal, Wood, Construction'	0.21
'Machinery'	0.45
'Chemicals and Textiles'	0.30

Note: All values are statistically significant after being randomised for 999 permutations

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

The results confirm moderately positive levels of spatial concentration which are higher in the ‘Machinery’ kind of clustering and lower in the ‘Metal, wood and construction’ type of clustering.

4.3 Cluster performance: Wages

Finally, we examine the performance of regions with clusters (defined as previously) when it comes to sectoral wages, in relation to the country to which they belong. Wages are often used as a proxy for productivity when attempting to examine whether concentrations of economic activity (mainly employment) are linked to higher performance. For an overview of related work see Fu and Ross (2013).

In order to control for the country effect we use the following ratio:

$$\frac{Sectoral\ Regional\ Wage^{11}}{Country\ Wage^{12}}$$

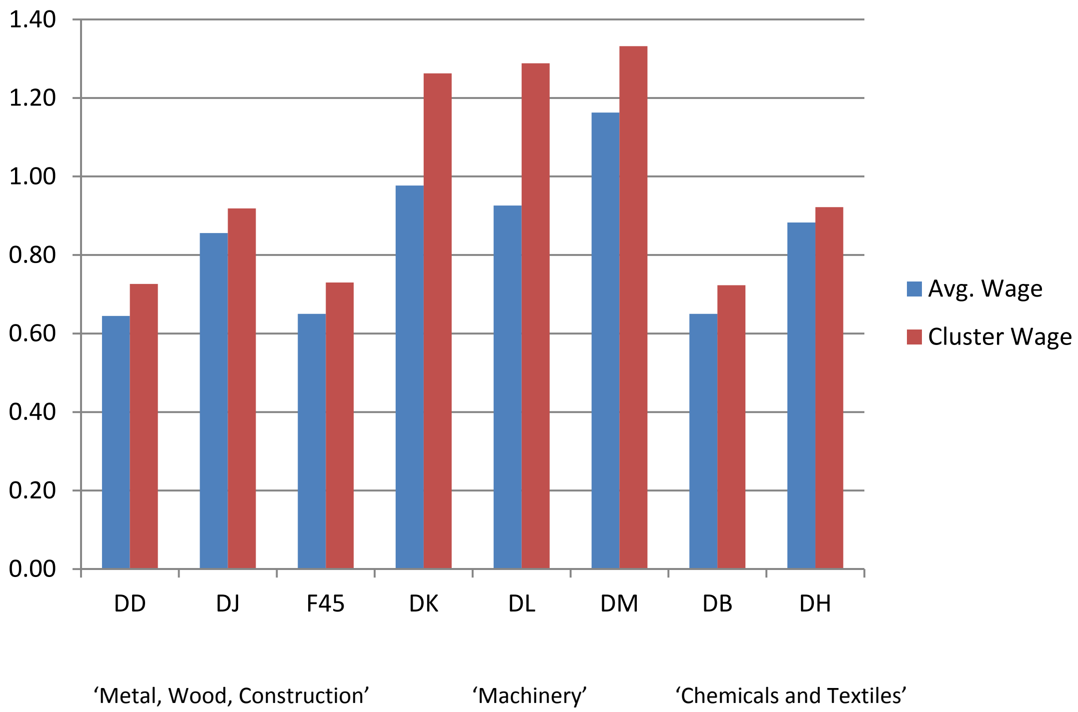
In the case of the Metal, Wood, Construction’ clusters, the relevant sectors (based on our PCA output) are Wood and Wood Products Manufacturing (DD), Basic Metals and Fabricated Metal Products Manufacturing (DJ) and Construction (F45).

In regards to the ‘Machinery’ clusters we look at Machinery and Equipment Manufacturing (DK), Electrical and Optical Equipment Manufacturing (DL) and Transport Equipment Manufacturing (DM).

The relevant sectors for the ‘Chemicals and Textiles’ cluster type are Textiles and Textile Products Manufacturing (DB) and Rubber and Plastic Products Manufacturing (DH).

[11] Eurostat database used: Structural Business Statistics (sbs_r_nuts03)
[12] Eurostat databases used: GDP and main aggregates (naida_10_gdp), Labour Force Survey (lfsq_eegaed)

Figure 5: Cluster sectoral wages compared to country sectoral wages



In Figure 5 we observe that that in every sector relative wages are higher in the regions with clusters, with the difference appearing significantly higher in the case of the sectors related to 'Machinery' clustering. This finding is consistent with the literature arguing that clustering tends to be associated with higher wages, an attribute which, in this context, can arguably be perceived as pointing towards higher cluster productivity.

5. Discussion

The results demonstrate that certain types of related patenting and manufacturing activity tend to co-locate at the regional level. A region, for instance, with a high concentration of employment in manufacturing of machinery (DK) is much more likely to have a high concentration in patents related to machinery (F01) and basic electric elements (H01) than in an unrelated patent sector. While a significant degree of technological relatedness is apparent in each cluster, the picture that emerges is arguably one which points towards the concept of related variety and not of narrowly defined specialisation.

Our results are consistent with the findings of studies which underline that while value chains are increasingly subject to fragmentation, parts of them remain considerably embedded in regional systems (Cusmano et al. 2010). The globalisation of production has been expanding for decades. However, this trend, it has been argued, has not been as strong when it comes to manufacturing processes with a certain level of complexity, where firms often have the incentive to keep their R&D and certain manufacturing activities close together, in order to benefit from deeply rooted knowledge clusters, a high quality workforce, established networks of suppliers, etc. (Simon et al. 2008). At the European level we find that a geographical pattern of co-location emerges. Our cluster indicator scores indicate that there is a significant distinction between 'core' and 'periphery' countries, with regions in the former scoring overwhelmingly higher in every type of cluster. It is worth underlining that three Spanish regions (Comunidad de Madrid, Cataluña and Comunidad Valenciana) were the only ones from periphery countries with more than 200 patents per year.

Apart from countries from the so-called 'core', Swedish regions also tend to score highly, while in Italy there is a chasm between the north and the south, with the former performing notably better.

The types of clusters produced by the application of our methodological approach appear consistently linked to higher wage performance in the related sectors.

Our indicator can be viewed as capturing historical industrialisation trajectories at the regional level. This includes 'lock-in' effects depicted by negative scores, which indicate that in regions where a certain type of cluster is present, certain other sectors tend to be underdeveloped, e.g. the electronics sector in the 'Chemicals and Textiles' cluster type. It would be interesting to delve deeper into these path dependency patterns, and future work could attempt to do so by gathering data for different points in time, producing a dynamic outline of the evolutionary path of regional economies.

Further research could also include adopting an even more holistic perspective, incorporating, for instance, data related to industrial output, trademarks and services employment. A more fine-grained approach could allow for the depiction of newly emerging innovative clusters, utilising bibliometric data to capture the future potential to produce technologies.

This would provide a useful policy tool by helping to identify areas where specific kinds of policy initiatives can be expected to effectively build upon existing and developing innovation capacity. Such a tool is especially relevant in the era of industry 4.0, since it offers a means of encapsulating the rapid transformations of industrial structures.

6. Conclusion

We have observed that, in the period under study, certain types of related patenting and manufacturing activity tend to co-locate, with the degree of cognitive proximity between patent and employment sectors arguably pointing towards the presence of a certain level of related variety. The co-location of patenting and manufacturing concentration appears to support the argument that knowledge-intensive parts of supply chains can resist outsourcing, since they depend crucially upon regionally embedded knowledge infrastructure, and interactive learning between the production and usage of new technologies.

Our findings also seem to support the theory related to the higher economic performance of clusters, in terms of higher sectoral wages.

Regarding the potential for future research, it would be interesting to apply a similar methodology for more recent years in order to present a dynamic depiction of the clustering process at the regional level. Acquiring such a picture of the underlying dynamics of innovation clustering may also assist policy-makers in their attempts to perform policy interventions aimed at the support of innovation and regional growth.

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