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A geography of corporate knowledge flows across world regions: evidence from patent citations of top R&D-investing firms

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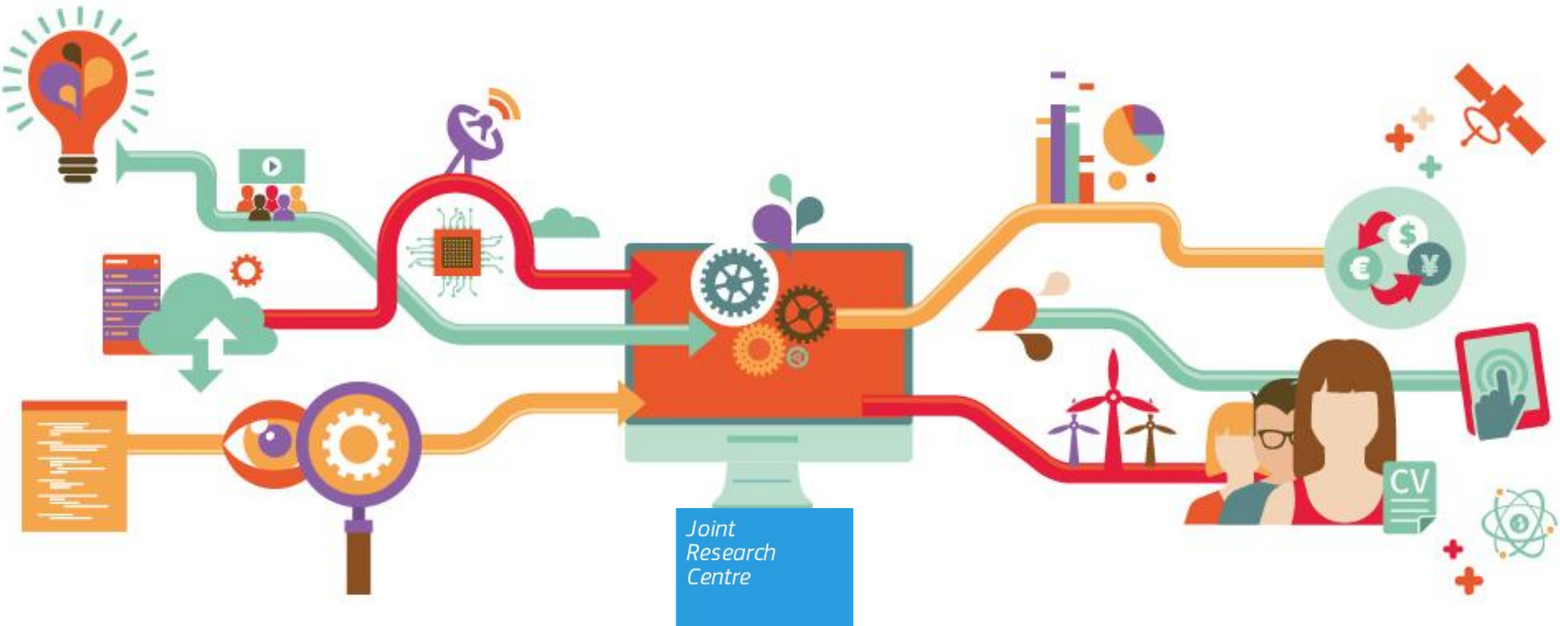

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This Working Paper is issued within the context of the Technology and Innovation Challenges 2030 (TIC 2030) project carried out by the European Commission's Joint Research Centre (Directorate B Growth & Innovation). The TIC 2030 project comprises three streams: one on the territorial dimension of technology analyses (KeyTer: Key Enabling and Emerging Technologies for Territorial Development and Competitiveness), one on developing and apply a novel method to analysing and forecasting economic development based on the dynamics of technologies and knowledge (COMPLEXITY: Economic Complexity for industrial competitiveness and innovation), and one on improving the understanding of industrial R&D and Innovation in the EU (GLORIA: Global Industrial Research & Innovation Analyses, and Complexity Project). The latter is carried out jointly with the Directorate General for Research and Innovation - Directorate A, Policy Development and Coordination.

A geography of corporate knowledge flows across world regions: evidence from patent citations of top R&D-investing firms [1]

Mafini DOSSO[2] and Didier LEBERT[3]

Abstract

This exploratory study looks at the structural and geographical patterns of corporate knowledge flows from a regional perspective. The methodological approach combines the centrality indicators developed in the social network analysis (SNA) and complementary tools from the graphs theory to assess the betweenness centrality of regions (or poles) – their ability to control knowledge flows within a network or to impact its cohesiveness – and the relative contribution of individual firms (or layers) to the centrality of regions. The combination of the two approaches brings relevant insights on the way large R&D-driven firms organise their knowledge sourcing and generation across world regions.

Keywords: patent citations; knowledge flows; graphs theory; regions; top corporate R&D investors.

JEL Classification: L14, O33, R58

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[1] This Working Paper is issued in the context of the GLObal Research and Investment Analysis (GLORIA) activities that are jointly carried out by the European Commission's Joint Research Centre (JRC) – Directorate B, Growth and Innovation and the Directorate General Research and Innovation - Directorate A, Policy Development and Coordination.
The views expressed are purely those of the author and may not in any circumstances be regarded as stating an official position of the European Commission.

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I. Introduction

The position of regions and local actors within knowledge and innovation networks matters for regional innovation and economic performances (Bathelt et al 2004, Sebestyén and Varga 2013, Autant-Bernard et al 2014, Huggins and Thompson 2014, Wanzenböck and Piribauer 2016). Hence, understanding the structural and organizational patterns shaping the acquisition and creation of knowledge at the local and regional levels is important to apprehend the differences in regional innovation capacities.

This study uses patents and patent citations to investigate the interregional patterns of the knowledge flows initiated by top corporate R&D investors (EU Industrial R&D Investment Scoreboards). [4] It assesses the importance of different regions in a given technological space and the relative contribution or influence of domestic and non-domestic firms to the positons of regions. Then, examples from selected firms are used to illustrate the outcomes in terms of firms' networks across regions. The empirical analysis exploits the tools from the social network analysis (Freeman 1979, Wasserman and Faust 1994, Borgatti 2005, Borgatti and Everett 2006) and the theory of graphs to assess the centrality of regions, of, and the relative contribution of top corporate R&D investors to the centrality of regions. In particular, we evaluate the betweenness centrality[5] of regions within the matrix of technological knowledge flows. Here, the betweenness concept refers to the position of a node or an actor for controlling the flow of knowledge within the network; this is known as the gatekeeper approach (see Wanzenböck et al 2014 for a regional application). From a graph theoretic perspective, a similar reasoning is employed to assess the contribution of specific layers (firms) of the matrix to the structure of the interregional flows.

In the present study, this approach is applied to the regionalized patents applications of top corporate R&D investors worldwide (European Commission, 2013) at the European Patent Office (EPO) between 2010 and 2012. For the purpose of the study, this latter dataset is combined with the REGPAT database of the OECD, which gives the patent records at the regional level. We further match their citations to prior EPO and Patent Cooperation Treaty or PCT patents. Our final dataset refers to more than 1,000 corporate R&D investors and covers EPO citations (citing and cited patent with the geographical location) and PCT (cited patent with the geographical location). The dataset refers to 495 territories or regions[6].

Section 2 overviews the main works relying on patent citations data to study the spatial and technological patterns of knowledge flows. Section III presents the dataset and methodological approach. Then the procedure used to complement the betweenness centrality indicator of the SNA with the graph theory toolbox is described. Section IV presents the centrality rankings and results of the application of our approach to the regionalized citations data of top corporate R&D investors. Section V concludes.

[4] As ranked in the 2013 EU Industrial R&D and Investment Scoreboard. Annual reports and R&D data are available at http://iri.jrc.ec.europa.eu/scoreboard.html

[5] See Borgatti and Everett 2006 for a cross-classification of centrality measures

[6] The names of regions are provided in Annex 2

II. Patent citations and network analysis to assess the centrality of regions

II.1 Patent citations to proxy for knowledge flows: overview of the literature

The use of patent citations data to study the diffusion of knowledge has given rise to a flourishing literature following the seminal works of Jaffe et al (1993). The basic rationale is twofold. First, the relation between the cited and the citing patent can be relevantly used to partially portray the direct or indirect knowledge flows between individual organisations, inventors or institutions. Second it is possible to add a geographical dimension to this relation. In other words, the geographical localization of the inventors of the cited and citing patents can be used to map the geographical or spatial distribution and diffusion of knowledge flows or spillovers (among other, Jaffe et al 1993, Jaffe and Trajtenberg 1999, 2002, Verspagen and De Loo 1999, Jaffe et al 2000, Maurseth and Verspagen 2002, Verspagen and Schoenmakers 2004, Peri 2005, Rave and Goetzke 2013). Critical reviews and discussions about the use of citations in this framework can be found in the studies of Michel and Bettels (2001), Gay and Lebas (2005,) Alcacer and Gittelman (2006). The empirical analyses typically use the geographical (location of inventor) and technological (patents classes) information provided in the patent documents and investigate the aggregate citation flows at the sector, technological field/domain, region or country levels.

One of the most robust finding relates to the spatial or geographical concentration of knowledge flows. In other words, knowledge tends to spill over relatively close locations. This finding has been confirmed at the country (e.g. Jaffe et al 1993, Jaffe and Trajtenberg 1999) and regional levels (Maurseth and Verspagen 2002, Verspagen and Schoenmakers 2004), mainly using patent data from the United States Patent and Trademark Office and the European Patent Office. For instance, Maurseth and Verspagen (2002) construct a region-by-region citations matrix and show that more knowledge flows within European countries than between European regions located in different countries. In addition to the significance of (smaller) geographical distances for the scope of spillovers, they confirm the importance of characteristics such as language, industry structure and technological specialisation for the technological interaction between regions. The study of Verspagen and Schoenmakers (2004) examines the patterns of world's largest MNE patenting from European regions. They confirm the geographical concentration at the corporate level, also for the extent of knowledge flows or the spatial character of patent citations. In other words, and for intra- and inter-firm flows, patents citations are more likely to take place between units that are located relatively near to each other (Verspagen and Schoenmakers 2004). Moreover, they are also able to detect a narrowing down of the scope of knowledge flows over time.

Verspagen and De Loo (1999) combine the sectoral and time dimension in their analysis of the R&D spillovers between sectors. The matrix of technological flows integrates the information from patent citations to assess the R&D spillovers between sectors. A key finding relates to the time lag required for the distribution of R&D spillovers.

At the sub-field level, Fontana et al (2009) use patent citation networks to study the dynamics of technical change in Ethernet. Their main insight is that patent citation are an appropriate information source to better understand the cumulativeness associated to the development of a technology as well as the discontinuities punctuating the trajectories

(Fontana et al ibid.). More recently, the analysis of Rave and Goetzke (2013) on mobile air-conditioning sector shows that most knowledge flows intra-nationally; across countries, they also remain concentrated among few places.
Furthermore, a growing number of studies that consider citations as useful and relevant proxy for knowledge flows, have looked at the determinants of knowledge flows (e.g. Aldieri 2011, Azagra-Caro and Consoli 2014, Aldieri and Vinci 2016), their effects (e.g. Peri 2005), while other works have used citation data in order to compare the quality of patents (e.g. Trajtenberg, 1990, Moed et al., 2004, Hall et al., 2005).

II.2. Applying network centrality analyses to patent citations data

As underlined above, the use of citations to better understand the patterns of technological flows across territories has been widely used by prior studies. The advances in social networks analysis provide a wide range of opportunities to investigate the structural properties of citations-based networks.
Since the seminal contributions of Freeman (1979) and Friedkin (1991), the literature has focused on the concept of centrality as a proxy to assess the involvement, critical positioning or contribution of a specific node or actor to the structuring or cohesiveness of the network (Wasserman and Faust, K. 1994, Costenbader and Valente 2003, Valente et al 2008, and see Borgatti 2005, Borgatti and Everett 2006 for detailed discussion of the conceptual foundations of centrality measures, Wanzenböck et al 2014 for an application to framework programs projects, co-publications and co-patents).
In this framework, at least three types of centrality measures, among the most employed - *degree, closeness,* and *betweenness* – can be distinguished (Freeman 1979, Borgatti and Everett, 2006). In simple terms, the degree centrality counts the number of edges, links or ties incident upon a node; the closeness centrality reflects the sum of distances from all other nodes, where the distance from a node to another is defined as the length (in links) of the shortest path from one to the other; the betweenness centrality tells us about the number of times any actor requires another actor (which centrality is being measured) to reach a third actor *via* the shortest path (Freeman 1979, Borgatti 2005, Borgatti and Everett 2006). Two approaches can be broadly distinguished, which bring apart radial type of measures (eg. degree and closeness) and the medial ones that assess the contribution of a node or an actor to the cohesion[7] of the network (Borgatti and Everett ibid.). According to the authors, the medial measures appear particularly relevant when networks are characterised by an important variation in local density. We adopt a similar measurement framework to our patent citations-based networks; that is the centrality of a region refers to

[7] The term cohesion in the networks analysis should be distinguished from Cohesion as an objective of the EU regional policy, which aims at “overall harmonious development”, among other, by reducing the disparities between regions. The cohesion in our empirical framework refers to the betweenness of nodes, and can be defined by the number of nodes/poles and the intensities of links and feedback effects in a network needed to connect the whole structure. In our framework, the more central a node/pole (region) or a layer (firm) is, the greater the impact it has on the cohesion of the given network.

its potential for withholding or disrupting flows or to act as a gatekeeper for the inflows of technological knowledge (see also Wanzenböck et al 2014).

In parallel of the social network analysis, a stream of literature has exploited the influence graph theory to analyse the structural properties of networks involving directed and weighted flows (Lantner 1974, Defourny and Thorbecke 1984, Lantner 2001, Lantner and Carluer 2004, Lantner and Lebert 2015). Although we do not show the linear algebra details here (see Lantner and Lebert 2015), we provide further below an example of the transformation of the territorial flows matrix into a citations graph and a matrix of influence. This latter matrix is the main input for the computations of centrality values.

III. Dataset structure and methodological approach

III. 1. Data sources

For the purposes of the structural analysis, we combine patents information from three different data sources.

- The EPO's PATSTAT[8] database is a worldwide statistical database, which contains patent applications from more than 80 countries. The autumn 2014 edition is employed for our analyses (European Patent Office, 2014). The database contains more than 80 million records and provides information on the patent application such as the inventors and owners, technology classes, titles and abstracts, publication instances, and citations.
- The OECD REGPAT dataset gives patent applications published by the EPO (derived from PATSTAT) and by the World Intellectual Property Organization (WIPO)[9] under the Patent Co-operation Treaty[10] (PCT patents at international phase). The patent filings are linked to more than 5 000 regions using the addresses of the inventors or applicants (covering regions from selected countries outside the OECD area). The dataset covers regional information for most OECD and EU28 member countries and the BRICS. It allows patent data to be used in connection with information such as citations, technical fields as well as with other regional data such as GDP or labour force statistics (see Maraut et al 2008 for technical details on the database). We use the February 2016 edition of REGPAT database.
- The patent data matched by the European Commission's JRC and the OECD provides, for the period 2010-2012, the applications of the top 2000 corporate R&D investors

[8] More info on PATSTAT can be found at http://www.epo.org

[9] The WIPO is an intergovernmental organisation responsible for the administration of several multilateral treaties on the legal and administrative aspects of intellectual property. In the patent area, the WIPO is in charge, among other, of the administration of the Paris Convention, the Patent Cooperation Treaty (PCT) and the International Patent Classification system (IPC).

[10] "The Patent Cooperation Treaty (PCT) assists applicants in seeking patent protection internationally for their inventions, helps patent Offices with their patent granting decisions, and facilitates public access to a wealth of technical information relating to those inventions. By filing one international patent application under the PCT, applicants can simultaneously seek protection for an invention in 148 countries throughout the world." (http://www.wipo.int/pct/en/index.html, August 3rd, 2016). The PCT system is administrated by the World Intellectual Property Organisation (WIPO).

worldwide, as ranked in the 2013 EU Industrial R&D Investment Scoreboard[11] (European Commission, 2013). The matching of their patents (and trademarks) has been performed in the frame of a joint project of the JRC and the OECD (see the report by Dernis et al 2015 for detailed statistics and analytical insights). Patent data have been retrieved from the PATSTAT database and the procedure has been carried out on a by-country basis using a series of string matching algorithms contained in the Imalinker system (Idener Multi Algorithm Linker) developed for the OECD by IDENER, Seville, 2013. [12] The procedure integrates information from the Scoreboard companies and their subsidiaries (about 500,000 subsidiaries) provided by the Bureau Van Bureau van Dijk's ORBIS database[13]. The patent applications have been associated to their ultimate owner.

Our final dataset is constructed as follows.
REGPAT provides information on 375,542 patent applications at the EPO between 2010 and 2012. Patent are assigned to the regional address[14] of the inventors and are selected according to the priority date. While the former allows to trace back where the invention was made, the priority year or first filing date is the closest to the actual date of invention (Maraut et al 2008), and thus from the actual occurrence of the knowledge flows. The dataset includes the patent applications of top corporate R&D investors at the EPO on the period 2010-2012. Only patents containing information on the inventor regional address and the International Patent Classification (IPC codes), allowing for the identification of the areas of technology to which patents pertain, are covered by the analysis. The merged dataset consists of 29,290 unique patent applications by 1006 top corporate R&D investors, i.e. about one fourth of the corporate patent data is geographically and technologically localizable.
Moreover, in order to prevent the double counting of patents from the same family – i.e. the filings/applications in different jurisdictions for the same invention –, the initial set of patents are further combined into 28, 477 International Patent Documentation Centre or INPADOC's patent families (via PATSTAT) for the 1006 scoreboard companies (for more detailed discussion on the concept of patent family, see Webb et al. 2005, Bakker et al. 2016).
A further step consists in extracting the citation information from the sampled patent families. A patent application may cite other patent publications, as well as non-patent literature (e.g., scientific literature). The second type of citations is not considered in the perimeter of the analysis as only corporate patents data are matched. Due to the period of application of patents by top corporate R&D investors (2010-2012), we cover only backward citations[15] or citations to previous patent documents. Accordingly, 57,234 EPO

[11] Detailed information and statistics on the sample of companies included in the annual EU Industrial and R&D Investment Scoreboards are available at http://iri.jrc.ec.europa.eu/scoreboard.html.
[12] More info on IMALINKER can be found at http://www.idener.es/?portfolio=imalinker
[13] ORBIS database is a private database providing private company information on financials, corporate structure, M&A deals, etc. More info is available at http://www.bvdinfo.com/en-gb/our-products/company-information/international-products/orbis
[14] This is especially important for the type of companies analysed here, as many patents are filed by large companies having several establishments or subsidiaries located in different regions and countries.
[15] Two groups of indicators can be constructed with citations. The first is based on backward citations, which are useful to assess the degree of novelty of the invention and knowledge transfer patterns (e.g. citation networks). The second is impact-type indicators, based on forward citations (OECD 2009).

citations (citing and cited patent families with the geographical location) and PCT (cited patent family with the geographical location) to 44,430 unique cited families are identified. The citations refer to 495 territories or regions defined according to the Nomenclature of territorial units for statistics[16] (NUTS) level 2 and to 591 technological classes or IPCs at the 4 digit level[17]. Finally, fractional counting of the patent families and the related citations (see box further below for an applied example) are used in reference to multiregional inventorship (related regional weights are provided on the OECD REGPAT) and in multiple classes cases (Maraut et al 2008).

Caveats to consider when using patent and patent citation data

Although patent data offer rich and consistent information on the technological content and location of inventive activity across long time periods, they entail several shortcomings that should be kept in mind in both the analytical and interpretative steps (Griliches 1990, Brusoni et al 2006, OECD 2009). First the use of patents greatly differs across sectors and firm size. Indeed, the pharmaceutical and semiconductor industries would appear as relatively appropriate candidates for this use. Whereas, it may be less appropriate in industries where alternative intellectual property protections prevail (e.g. services) or when the invention is simply not patented, though further leading to a successful innovation. Second, due to the patenting costs and time resources, large firms tend to recourse to a greater extent to patents than small firms would do. Third, patents entail different market potential and are not of equal monetary value; indeed, more than one third of patents is neither commercially exploited within the patent-holding organization nor licensed to other organizations (Brusoni et al 2006). Last but not least, firms may apply for patent for strategic purposes that are different from the legal protection of an invention (Blind et al. 2006, Torrisi et al 2016). Bearing in mind these limitations, patents nevertheless constitute a relevant and unique proxy to study the inventive activities of companies (Acs and Audretsch 1989, OECD 2009, de Rassenfosse et al. 2013). Further treating patent data as relational data, through for instance citations, gives considerable possibilities to analyse the patterns and dynamics of regional knowledge and innovation networks (Ter Wal and Boschma, 2009). We briefly remind the related limitations below.

In relation to patent citation data, several limitations should also be underlined. They relate to the inherent nature of citations and patents. First as only citations made so far are known, this leads to systematic truncations in the number of citations. In other word, there is always the risk that the bulk of citations to a particular patent come or would come later in the stages of technological development.

Second citation practices differ across offices, which may lead to different citation intensities (see details in OECD 2009), reflecting examiners rather than firms or inventors' behaviours (Alcacer and Gittelman 2006 on USPTO citations data). This is particularly important in the present context where the coverage is limited to EPO (and PCT for cited), where the citations to prior art, known as the "duty of candour", are optional (OECD 2009). It implies

[16] The NUTS nomenclature subdivides the economic territory of the European Union (EU) into regions at three different levels (NUTS 1, 2 and 3 respectively, moving from larger to smaller territorial units). Above NUTS 1, there is the 'national' level of the Member States. A section dedicated to the NUTS can be found at http://ec.europa.eu/eurostat/web/nuts/overview

[17] See at http://www.wipo.int/classifications/ipc/fr/

that most citations may be added during the examining phase, thus citations are inherently a very noisy measure.
Third, as underlined by Hall et al (2005), there is a kind of citation "inflation" as more patents are combined with more citations, suggesting that later citations are less significant than earlier ones from a statistical perspective (Hall et al ibid.).
Fourth, as for the patents they relate to, the citations show technological and sectoral specific patterns partially due to the degree of technological dependence or cumulativeness in the given technological field or industry; thus backward citation intensities will inherently differ across technologies and industries.
However as underlined by the OECD (2009), citations yield relevant opportunities to analyse the origins, the evolution of technologies and the diffusion of knowledge between inventing organizations or individuals, institutions and geographical areas. Furthermore, and this is the case for the present study, several studies following the seminal works of Jaffe (1986) and Jaffe et al (1993), confirm that an appropriate and careful use of citations data can reveal key patterns of knowledge flows and spillovers, thus greatly contributing to our knowledge on how technologies are created and diffused over time and space (see for instance, Jaffe and Trajtenberg 1999, Gay and Lebas 2005, Sorenson et al 2006, Ter Wal and Boschma 2009, Aldieri 2011).

III.2 Data structure and main indicators

We use the regionalized backward citations of top corporate R&D investors to build up the aggregated matrices of technological flows between regions. They serve as the primary input to assess among other (i) the centralities of regions within the interregional knowledge flows and (ii) the relative influences of individual firms on the positioning of individual regions. As show in the figures 1 and 2, the rows of the matrix correspond to regions to which the cited patents are assigned to, while the columns of the matrix refer to the citing patents[18]. Each generic element or cell measures the extent (or weight) of the technological knowledge inflows from region *i* to region *j*. These matrices can be disaggregated in several layers – technologies (figure 1) or firms (figure 2) – or related aggregates (industries and countries of headquarters and, technological domains or fields). The flows from a region towards another region are quantified employing a procedure that breaks down every citation according to the weight of a relation *region x region x citing firm* or *region x region x technology*. These matrices constitute the main input for the data treatment[19] and computations of the indicators presented later on.

[18] Note that two additional matrices can be constructed, where the front rows and columns would represent respectively, the cited and citing technology (ies) and the layers: origin and destination territories or citing firms. However the primary matrix cannot be generated for the firms as only the citing patents have been assigned to the individual scoreboard companies, i.e. the cited patents cannot be traced back to a scoreboard company.
[19] The matching of citations data of top R&D spenders' patents has been performed *via* PATSTAT at the European Commission JRC Seville (Spain) and the programing and data treatment (matrices design, construction and computation of indicators, generation of output table, data storage, etc.) have been performed on MATLAB® within the Unité d'Économie Appliquée, ENSTA ParisTech at the University of Paris-Saclay, Paris (France).

In reference to the figure 1, the box (pp. 11-12) further below provides an example of the construction of a technological flow matrix at the level of a single region and then, the procedure used to build up the influence matrix.

Figure 1: landscape region x region x technology

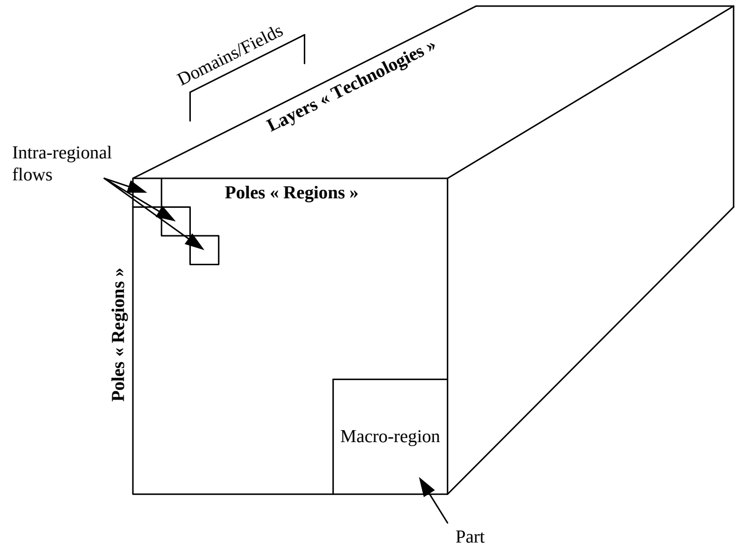
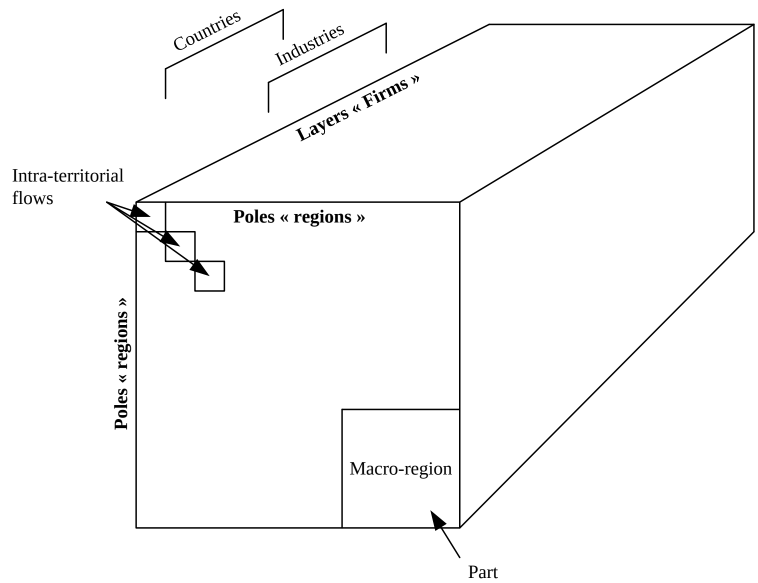


Figure 2 : landscape region x region x firm



Box: From knowledge flows to influence matrices

We consider a patent B, within inventors located in territories 2, 3 and 4, citing a patent A which has inventors' addresses in territories 1, 2 and 3. Besides, let us assume the following inventorship patterns apply: patent A claims inventorship in territories 1 (1 time), 2 (3 times) and 3 (2 times) and the patent B claims inventorship in territories 2 (2 times), 3 (1 time) and 4 (1 time).
The links going from territories 1-2-3 towards territories 2-3-4 can be broken down into 24 parts (6 references to territories in patent A and 4 in patent B and then 6x4=24); in this simple setting the link from territory 1 to territory 2 is equivalent to one twelfth (= (1 time as cited x 2 times as citing)/24), while the link from territory 2 to territory 2 is equivalent to one fourth (= (3x2)/24), etc. The values of the links for this (and for every) citation sum up to 1.

In the framework of Figure 1 (territory x territory x technology), the patent B refers to two technological classes (tech 1 and tech 2), which are assumed to be distributed across links. The technologies in Figure 1 are the layers and the participation of the citation A→B (B cites A) to one of the layer is detailed in Table 1 below. Therefore, for each layer (technology) and this citation, the values of the links sum up to 0.5.

	Territory 1	Territory 2	Territory 3	Territory 4	Total
Territory 1	0.0000	0.0416	0.0208	0.0208	0.0833
Territory 2	0.0000	0.1250	0.0625	0.0625	0.2500
Territory 3	0.0000	0.0833	0.0416	0.0416	0.1666
Territory 4	0.0000	0.0000	0.0000	0.0000	0.0000
Total	0.0000	0.2500	0.1250	0.1250	0.5000

Table 1. Example of a matrix of technological flows related to the tech 1 or tech 2 (figure 1)

How to read: *knowledge flows go from territories in row (cited) to columns (citing). For instance, when B cites A, the value of flows from territory 1 to 2 correspond to 1/24 P (0.0416) for a given technology.*

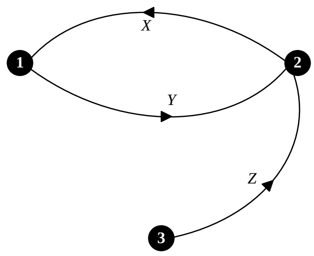
Note: The rationale is similar for region x region x firms matrices (figure 2). In all cases, the sum of values of the links is strictly equal to the number of citations structuring the landscape, in our case 57,234 EPO citations to EPO and PCT patents. The sum of the layers "technologies/ firms" to derive the aggregated matrix of territorial flows give the same result, and thus, the same centrality scores for the territories. Note that regions may refer to several micro-regions or sub-territorial divisions. In these cases, the region is accounted for as many times as distinct micro-regions are claimed.

The construction of influence matrices to assess the contribution of layers to the centrality of poles (regions)

The contributions of specific layers to the centrality of territories will be specified according to the given analytical unit (the nature of the layer, technology or firm). The margins of the aggregated matrix are used as a common denominator for all flows; this is true whatever layer is considered.
Let us now come back to the matrix of territorial flows and its transformation in citations graph and influence matrix (figure 3). In the territorial flows matrix, every row (cited territories) and column (citing territories) correspond respectively to the territories 1, 2 and 3 of the graph of interregional citations. Every cell of this matrix represents the citations flows X, Y and Z between these territories obtained by the aforementioned procedure.

_	*Y*	0
X	_	0
0	*Z*	_

Matrix of territorial flows



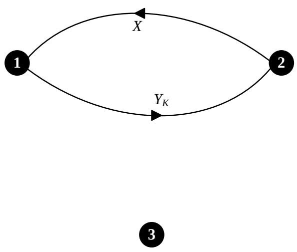
Graph of interregional citations

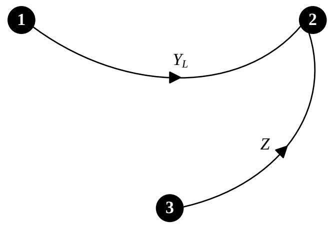
1	-y	0
-x	1	0
0	-z	1

Matrix of influence

Figure 3. From the territorial matrix to the influence matrix

The graph of interregional citations can be further broken down into flows internalized by two firms *K* and *L* (figure 2 and figure 3). The global graph above corresponds to the aggregation of the individual firms graphs. Here, $Y = Y_K + Y_L$ and the set of citations *X* are internalized by the firm *K* as the set of citations *Z* are internalized by the firm *L*.





_	Y_K	0
X	_	0
0	0	_

1	$-y_K$	0
-x	1	0
0	0	1

Firm K

_	Y_L	0
0	_	0
0	Z	_

1	$-y_L$	0
0	1	0
0	-z	1

Firm L

Figure 4. Disaggregation of matrices and graphs at the firm level

The transformation into an influence graph assigns weights (between 0 and 1) to single flows. It takes the form of a Leontief matrix. Values in the influence matrix synthetize the intensity of bilateral link between regions. For instance, if $x > y$ in Figure 3, the "direct dependence" of 1 in relation to 2 is stronger than the direct dependence of 2 in relation to 1. The same are applied to the layers in Figure 4 and to the main matrix in Figure 3, so that for example $y = y_K + y_L$.

More precisely, the deflators applied to flows matrices account for the maximums of the aggregated matrices between knowledge emission (row) and reception (column) for each row/territory. Therefore, two scenarios come up: either the territory emits more than it receives, thus the sum of coefficients obtained in row is strictly equal to 1; or the territory receives more than it emits, thus the sum of coefficients obtained in row is strictly inferior to 1. Consequently:

- The size differences between territories (area, population, etc.) are rubbed out due to the weighting schemes given that each territory is related to its own knowledge emission profile.
- When a territory shows a deficit in knowledge flows, the global weight of influences emissions is reduced by the related deficit weight. Doing so, we give here a relatively higher importance to net emitting territories.

The main indicators retained for the analysis are applied to the figures 1 and 2. They are summarized in Table 2.

- The betweenness centrality (or of cohesion) of a pole of the technological flow matrix: the centrality is the ratio between the diagonal co-factors of the influence matrix and the determinant of the matrix. The values obtained for each territory are superior or equal to 1. The more *central* the territory is, the more it creates cohesion within the represented network and the higher will be the ratio. The value of c_i corresponds to the extent to which the pole i internalizes the circuits / circularities within the flow matrix.
- The betweenness centrality of a layer (firm or technology). The basic principle consists in excluding from the aggregated structure the flows specific to each layer, which allows us to compute the determinants of the partial graphs. Their values increase as much as the given layers contribute to the global circularities. The value of c_j reflects the extent to which a given layer j contributes to create the cohesion between the poles i through the circularities of the flows matrix it internalizes.
- The contribution of the layers to the poles centrality. The exclusion principle holds again: by removing, for each layer, the flows related to a selected pole, we can derive a ranking of the different layers according to the circularities they internalize on the selected pole. In this perspective, at least two dimensions can actually contribute to the centrality of a pole: the technologies and the firms on the landscape regions x regions. The value of C_i^j represents the weight of the layer j in the cohesion the pole i creates in the flows matrix.

Table 2. Main indicators for the analysis of technological flows matrix

Betweenness centrality of the pole i: $c_i = \frac{d_{-i}}{d}$	d_{-i} is the determinant of the sub-graph excluding the pole i
Betweenness centrality of the layer j : $c_j = \frac{d_{-j}}{d}$	d_{-j} is the determinant of the partial graph excluding the layer j
Contribution of a layer j to the centrality of pole i : $C_i^j = \frac{d_{-i}^j - d}{d_{-i} - d}$	d_{-i}^j is the determinant of the partial graph excluding the flow of i in j

IV. Empirical observations

IV.1 Centrality of regions and top worldwide R&D-investing firms

The combination of network centrality analyses and firms' patent data at the regional level offers complementary tools for the assessment and benchmarking of regions' technological positions and for the identification of key actors both inside and outside the region. Tables 3, 4 and 5 provide the main results of our exploratory analysis. Then, we portray the spatial organisation of corporate R&D from an interregional perspective using the network illustrations from three firms.

Importantly, among the six main regions creating the cohesion on the European market for technologies, four are from Asia. While such result is driven by the specific sample composition, it also may reflect the specific industrial specialisation of Asian countries/regions (Japan, Korea) which show narrower technological scope and strong and attractive specific technological capabilities (e.g. ICT related, see Dernis et al 2015). The corresponding regions are indeed able to attract "well-connected" firms, which are able (based on in-house and external knowledge) to tap into a wide pool of geographically dispersed prior technological knowledge in order to produce new technological knowledge and to spread knowledge produced locally over a wide geographical space.

Expectedly, capital-regions present among the highest centrality scores. These territories belong to the densest transregional clusters, which often concentrate enough critical mass and opportunities for related diversification.

Table 3. The betweenness centrality of regions

Rank	Centrality score	Region code	Names of region	Country code	Number of patents families
1	1,1485	JPD	SOUTHERN-KANTO	JP	2768
2	1,0706	CH01	LEMANIC REGION	CH	278
3	1,0680	JPF	TOUKAI	JP	1002
4	1,0665	CH02	ESPACE MITTELLAND	CH	260
5	1,0660	KR01	CAPITAL REGION	KR	1586
6	1,0646	JPG	KINKI	JP	1144
7	1,0512	FR10	ILE DE FRANCE	FR	1019
8	1,0506	DE21	OBERBAYERN	DE	1107
9	1,0473	DE11	STUTTGART	DE	799
10	1,0456	DEA1	DUSSELDORF	DE	820
11	1,0431	US06	CALIFORNIA	US	757
12	1,0379	DK03	SYDDANMARK	DK	128
13	1,0360	DE71	DARMSTADT	DE	642
14	1,0340	CH04	ZURICH	CH	417
15	1,0321	DEF0	SCHLESWIG-HOLSTEIN	DE	282
16	1,0318	DE12	KARLSRUHE	DE	695
17	1,0316	FI1B	HELSINKI-UUSIMAA	FI	246

Rank	Centrality score	Region code	Names of region	Country code	Number of patents families
18	1,0311	JPC	NORTHERN-KANTO, KOSHIN	JP	438
19	1,0304	US09	CONNECTICUT	US	392
20	1,0303	DEA2	KOLN	DE	529
21	1,0291	DE60	HAMBURG	DE	227
22	1,0288	US39	OHIO	US	228
23	1,0284	DEB3	RHEINHESSEN-PFALZ	DE	344
24	1,0266	CA35	ONTARIO	CA	600
25	1,0260	CH03	NORDWESTSCHWEIZ	CH	289
26	1,0256	DE25	MITTELFRANKEN	DE	553
27	1,0241	ITC4	LOMBARDIA	IT	308
28	1,0233	FR71	RHONE-ALPES	FR	670
29	1,0232	DK04	MIDTJYLLAND	DK	254
30	1,0220	NL11	GRONINGEN	NL	7
31	1,0220	DEA5	ARNSBERG	DE	345
32	1,0214	NL12	FRIESLAND (NL)	NL	6
33	1,0203	US36	NEW YORK	US	345
34	1,0196	CH05	OSTSCHWEIZ	CH	238
35	1,0193	ITH4	FRIULI-VENEZIA GIULIA	IT	250
36	1,0192	NL41	NOORD-BRABANT	NL	260
37	1,0190	DK01	HOVEDSTADEN	DK	122
38	1,0175	US34	NEW JERSEY	US	330
39	1,0175	DE30	BERLIN	DE	314
40	1,0174	DE13	FREIBURG	DE	365

Table 4 shows the betweenness centrality values of the most central top R&D investors or the firms that contribute, to the greatest extent, to create the cohesion in the interregional knowledge flows. The table also provides their rank in the *The 2013 EU Industrial R&D Investment Scoreboard* (European Commission, 2013) as well as their industrial affiliation.

Table 4 suggests that the most central firms appear more geographically diversified than what one could have expected from the hierarchy of most central territories. This means that while (firms from) central territories may actually lead global technological development, less central territories can indeed assume multiple roles in the creation of knowledge at local and global levels. This supports further research in order to map the type and technological level of activities undertaken by large R&D investors beyond central regions or leading science and technology hubs.

At the industry level, leading firms reflect well the technological diversity in Europe, as well as the importance of industries related to consumer goods.

Table 4. The betweenness centrality of firms

Rank	Centrality score	Names of corporate R&D investor	RD Rank (SB 2013)	Nb patents	Country code	ICB code	ICB industry name
1	2,5076	SIEMENS	17	1464	DE	2733	Electrical Comp. & Equip.
2	1,6633	GENERAL ELECTRIC	32	764	US	2720	General Industrials
3	1,5094	VALEO	155	178	FR	3350	Automobiles & Parts
4	1,4116	AMER SPORTS	965	66	FI	3740	Leisure Goods
5	1,4058	PROCTER & GAMBLE	71	181	US	3720	Household Goods & Home Construction
6	1,3930	SAMSUNG ELECTRONICS	2	865	KR	2737	Electronic Equipment
7	1,3849	SWATCH	487	187	CH	3760	Personal Goods
8	1,3704	HONDA MOTOR	16	273	JP	3350	Automobiles & Parts
9	1,3570	ROBERT BOSCH	14	365	DE	3350	Automobiles & Parts
10	1,3117	BASF	63	179	DE	1350	Chemicals
11	1,2958	TOSHIBA	43	263	JP	2720	General Industrials
12	1,2952	ABB	95	462	CH	2757	Industrial Machinery
13	1,2931	RESEARCH IN MOTION	97	625	CA	9578	Telecommunications Equip.
14	1,2853	LG ELECTRONICS	56	342	KR	3743	Consumer Electronics
15	1,2776	FIAT	34	103	IT	3350	Automobiles & Parts
16	1,2757	DEERE	104	132	US	2753	Commer. Vehicles & Trucks
17	1,2377	UNITED TECHNOLOGIES	62	340	US	2710	Aerospace & Defence
18	1,2363	ALCATEL-LUCENT	49	533	FR	9578	Telecommunications Equip.
19	1,2317	VOLKSWAGEN	1	262	DE	3350	Automobiles & Parts
20	1,2286	HEIDELBERGER DRUC.*	621	64	DE	2757	Industrial Machinery
21	1,2229	CLAAS	447	105	DE	2753	Commer. Vehicles & Trucks
22	1,2199	METSO	591	66	FI	2757	Industrial Machinery
23	1,2173	KORBER	731	88	DE	2720	General Industrials
24	1,2139	MAKITA	911	102	JP	3720	Household Goods & Home Construction
25	1,2129	SONY	24	374	JP	3740	Leisure Goods
26	1,2102	VOITH	442	67	DE	2720	General Industrials
27	1,2101	OC OERLIKON	707	20	CH	2720	General Industrials
28	1,2091	PANASONIC	19	296	JP	3740	Leisure Goods
29	1,2036	STANLEY BLACK & DECKER	565	101	US	3720	Household Goods & Home Construction
30	1,1997	HITACHI	37	293	JP	2733	Electrical Comp. & Equip.
31	1,1965	ADIDAS	583	16	DE	3760	Personal Goods
32	1,1727	NESTLE	80	125	CH	3570	Food Producers
33	1,1707	BAYER	36	152	DE	4577	Pharmaceuticals
34	1,1697	BOREALIS	732	153	AT	1350	Chemicals
35	1,1680	KOITO MANUFACTUR.	458	45	JP	3350	Automobiles & Parts
36	1,1631	FUJIFILM	74	301	JP	2737	Electronic Equipment
37	1,1631	EADS	30	386	NL	2710	Aerospace & Defence
38	1,1577	HILTI	431	124	LI	2350	Construction & Materials
39	1,1492	HUAWEI	31	331	CN	9578	Telecommunications Equip.
40	1,1488	SEIKO EPSON	225	150	JP	9574	Electronic Office Equip.

IV.2 Regions and the firms: illustrations from top central regions and top central R&D investors

Table 5 shows the upper part of the ranking based on our third indicator. The contribution of the most central top R&D investors to the centrality of Southern Kanto (Japan), Lemanic Region (Switzerland) and Ile de France (France). As shown in Table 3, they feature among the top ten most central territories in creating network cohesion in the selected technological space. While there is no strong industrial determinism, the most central contributors are local groups; and this is very pronounced for Japan's regions and headquartered top R&D investors.

Tables 5. The contribution of firms (layers) to the centrality of regions (poles): selected regions

Southern Kanto, Japan

Rank	Centrality scores	Names of corporate R&D investors	RD rank	Nb patents	Countries' codes	ICB	ICB industry names
1	0,1127	HONDA MOTOR	16	273	JP	3350	Automobiles & Parts
2	0,1086	SONY	24	374	JP	3740	Leisure Goods
3	0,1064	TOSHIBA	43	263	JP	2720	General Industrials
4	0,0901	HITACHI	37	293	JP	2733	Electrical Components & Equipment
5	0,0883	FUJIFILM	74	301	JP	2737	Electronic Equipment
6	0,0648	CANON	44	239	JP	9574	Electronic Office Equipment
7	0,0604	RICOH	113	202	JP	9574	Electronic Office Equipment
8	0,0583	FUJITSU	55	193	JP	9533	Computer Services
9	0,0498	SAMSUNG ELECTRONICS	2	865	KR	2737	Electronic Equipment
10	0,0393	SEIKO EPSON	225	150	JP	9574	Electronic Office Equipment
11	0,0373	BROTHER INDUSTRIES	285	134	JP	9574	Electronic Office Equipment
12	0,0298	RESEARCH IN MOTION	97	625	CA	9578	Telecommunications Equipment
13	0,0255	SHIN-ETSU CHEMICAL	284	163	JP	1350	Chemicals
14	0,0237	PANASONIC	19	296	JP	3740	Leisure Goods
15	0,0216	SUMITOMO RUBBER INDUSTRIES	465	100	JP	3350	Automobiles & Parts
16	0,0194	LG ELECTRONICS	56	342	KR	3743	Consumer Electronics
17	0,0193	ALCATEL-LUCENT	49	533	FR	9578	Telecommunications Equipment
18	0,0191	MITSUBISHI HEAVY	198	45	JP	2720	General Industrials
19	0,0183	SIEMENS	17	1464	DE	2733	Electrical Components & Equipment
20	0,0182	OLYMPUS	181	88	JP	4530	Health Care Equipment & Services

Lemanic Region, Switzerland

Rank	Centrality scores	Names of corporate R&D investors	RD rank	Nb patents	Countries' codes	ICB	ICB industry names
1	0,7677	SWATCH	487	187	CH	3760	Personal Goods
2	0,3248	NESTLE	80	125	CH	3570	Food Producers
3	0,0949	KOENIG & BAUER	1109	22	DE	2757	Industrial Machinery
4	0,0502	PHILIP MORRIS INTERNATIONAL	294	26	US	3780	Tobacco
5	0,0346	KUDELSKI	505	34	CH	9537	Software
6	0,0285	STRYKER	268	33	US	4530	Health Care Equipment & Services
7	0,0243	SIEMENS	17	1464	DE	2733	Electrical Components & Equip.
8	0,0242	MEYER BURGER TECHNOLOGY	888	8	CH	2757	Industrial Machinery
9	0,0161	RICHEMONT	1107	6	CH	5370	General Retailers
10	0,0124	MONDELEZ	269	30	US	3570	Food Producers
11	0,0062	PROCTER & GAMBLE	71	181	US	3720	Household Goods & Home Constr.
12	0,0062	ASSA ABLOY	500	29	SE	2350	Construction & Materials
13	0,0061	GEORG FISCHER	885	27	CH	2757	Industrial Machinery
14	0,0058	B BRAUN MELSUNGEN	408	45	DE	4530	Health Care Equipment & Services
15	0,0053	GENERAL ELECTRIC	32	764	US	2720	General Industrials
16	0,0050	HEXAGON	351	76	SE	2757	Industrial Machinery
17	0,0049	SULZER	908	41	CH	2757	Industrial Machinery
18	0,0048	FRANCE TELECOM	134	64	FR	6530	Fixed Line Telecommunications
19	0,0047	ADVANCED DIGITAL BROADCAST	1561	17	CH	9578	Telecommunications Equipment
20	0,0045	SONY	24	374	JP	3740	Leisure Goods

Ile de France, France

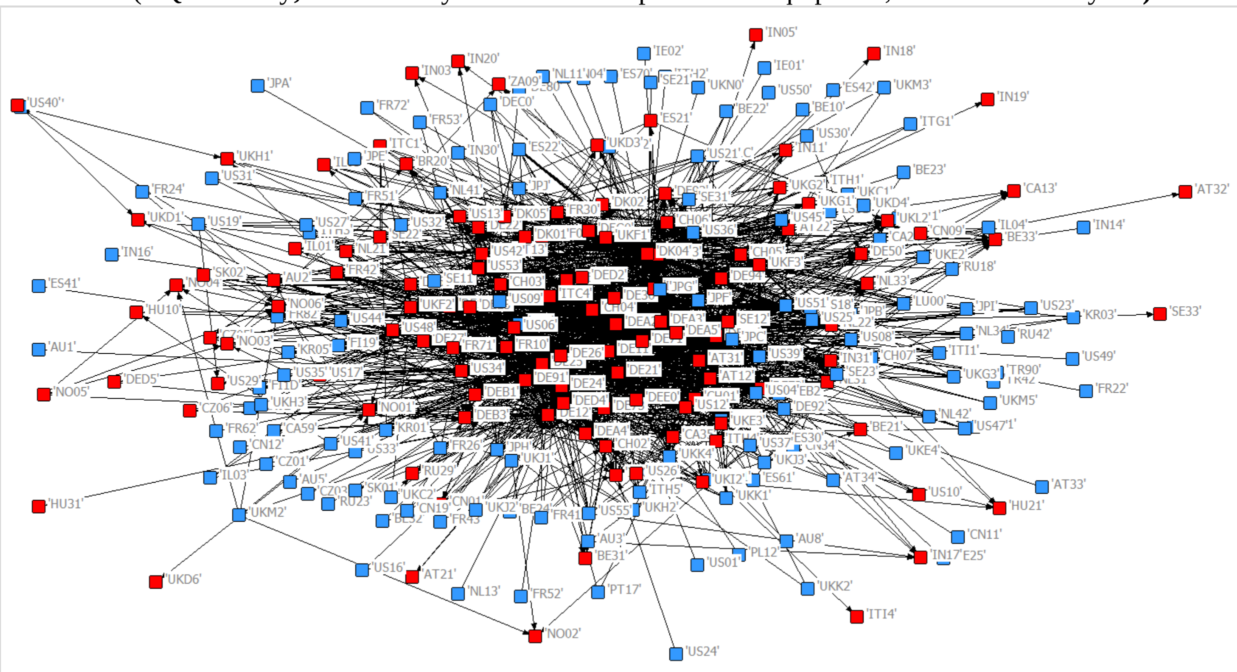
Rank	Centrality scores	Names of corporate R&D investors	RD rank	Nb patents	Countries' codes	ICB	ICB industry names
1	0,1548	VALEO	155	178	FR	3350	Automobiles & Parts
2	0,1204	ALCATEL-LUCENT	49	533	FR	9578	Telecommunications Equipment
3	0,0893	PEUGEOT (PSA)	48	108	FR	3350	Automobiles & Parts
4	0,0654	TECHNICOLOR	492	132	FR	5550	Media
5	0,0633	GEMALTO	461	125	NL	2737	Electronic Equipment
6	0,0598	LAIR LIQUIDE	436	119	FR	1350	Chemicals
7	0,0446	GENERAL ELECTRIC	32	764	US	2720	General Industrials
8	0,0427	SORIN	894	47	IT	4530	Health Care Equipment & Services
9	0,0381	THALES	157	139	FR	2710	Aerospace & Defence
10	0,0321	UNITED TECHNOLOGIES	62	340	US	2710	Aerospace & Defence
11	0,0314	SCHLUMBERGER	122	55	CW	570	Oil Equipment, Services & Distribution
12	0,0282	SIEMENS	17	1464	DE	2733	Electrical Components & Equipment
13	0,0276	RENAULT	58	25	FR	3350	Automobiles & Parts
14	0,0272	EADS	30	386	NL	2710	Aerospace & Defence
15	0,0267	SAFRAN	100	54	FR	2710	Aerospace & Defence
16	0,0248	SERVIER	126	15	FR	4577	Pharmaceuticals
17	0,0239	PRYSMIAN	892	36	IT	2733	Electrical Components & Equipment
18	0,0236	KUDELSKI	505	34	CH	9537	Software
19	0,0232	FIAT	34	103	IT	3350	Automobiles & Parts
20	0,0215	ALSTOM	121	55	FR	2757	Industrial Machinery

In order to further illustrate our results, we break down at the corporate level the interregional flows for the three most central firms: Siemens (Germany, Electrical Components & Equipment), General Electric (United-States, General Industrials) and Valeo (France, Automobiles & Parts). They constitute the top most contributing firms (or layers) to the cohesion of interregional knowledge flows in terms of betweenness centrality (Table 4). The red points correspond to the citing territories, where the knowledge is generated and the blue points represent the “pure” cited territories, where the knowledge is imported from. The thickness of the lines reflects the intensity of flows between the poles or regions.

A first observation is the high graph density that confirms the complexity of the territorial organisation of large R&D-driven firms. The figures also confirm the important (geographical) diversity of regional sources which top R&D investors rely upon in order to generate knowledge across fewer poles. This suggests that each region may actually have a role in technological development. Nevertheless, as illustrated by Foray et al, not all regions will be able to lead the basic inventions underlying general purposes technologies (GPTs).
In our framework, this means that not all regions should try to attract well-connected firms. A more realistic objective is to identify which firms render the region central and then which technologies and clusters of innovative activities are associated. The observed differences of density between the firms shown mirror differences both in the size of international technological activities, but also firm-specific networking and sourcing behaviours and strategies.

Figure 5 – Region and the firms: technological knowledge networks of R&D investors

SIEMENS (HQ Germany**;** ICB industry: Electrical Components & Equipment; Rank of centrality: 1st**)**

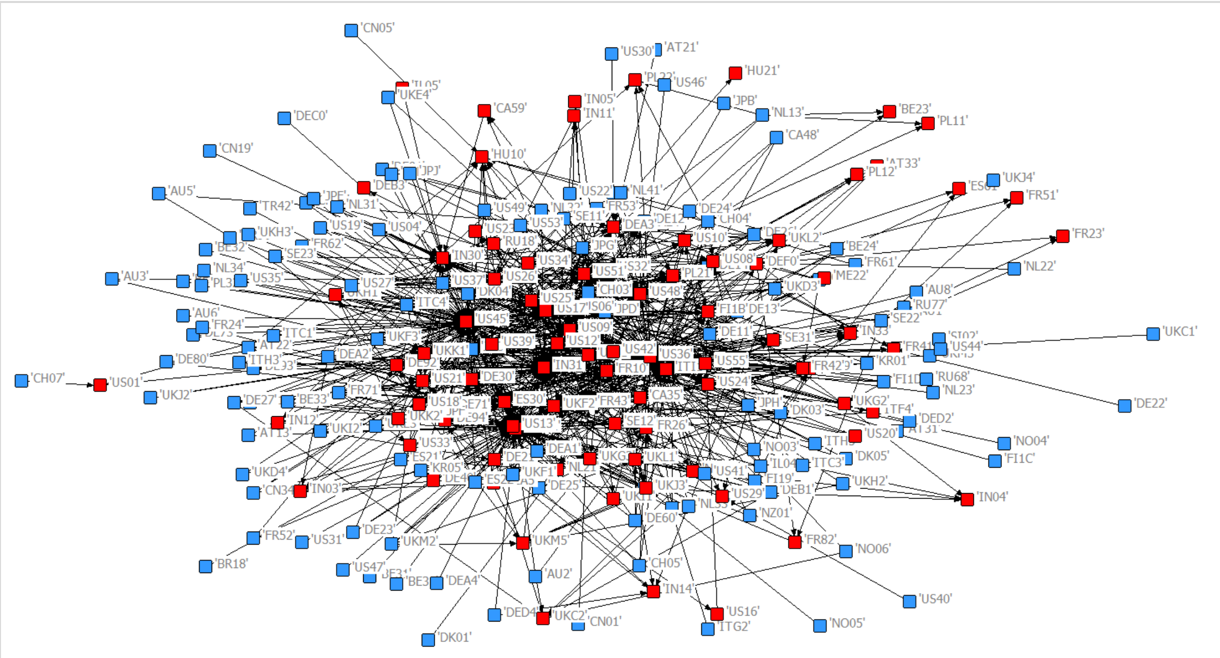


Besides the broad range of German regions, Siemens carries out knowledge generation activities across a number of European regions located, in particular, in the UK (eg. South Yorkshire, East Wales,), France (eg. Ile de France, Rhône Alpes), Austria (Oberã–Sterreich,

Niederã–Sterreich), Italy (eg. Piemonte, Liguria, Lombardia), Switzerland and Northern European regions mainly in Denmark, Sweden and Norway, Spain's Basque Country. Foreign regions are mainly located in the US and, to a lesser extent, in India (eg. National Capital Territory of Delhi, Kerala,) aside with the regions of Sao Paolo (Brazil), Shanghai and Beijing (China) and Western Cape (South Africa).
The blue points or pure sourcing regions further highlight the European origins of the firm, with an even broader Europe's regional base, and the key role of US regions' technological knowledge for Siemens. Japanese regions – Northern-Kanto, Koshin JPC, Southern-Kanto JPD, Hokuriku JPE, Toukai JPF and Kinki JPG – also appear to have an important role in the technological knowledge production of Siemens.

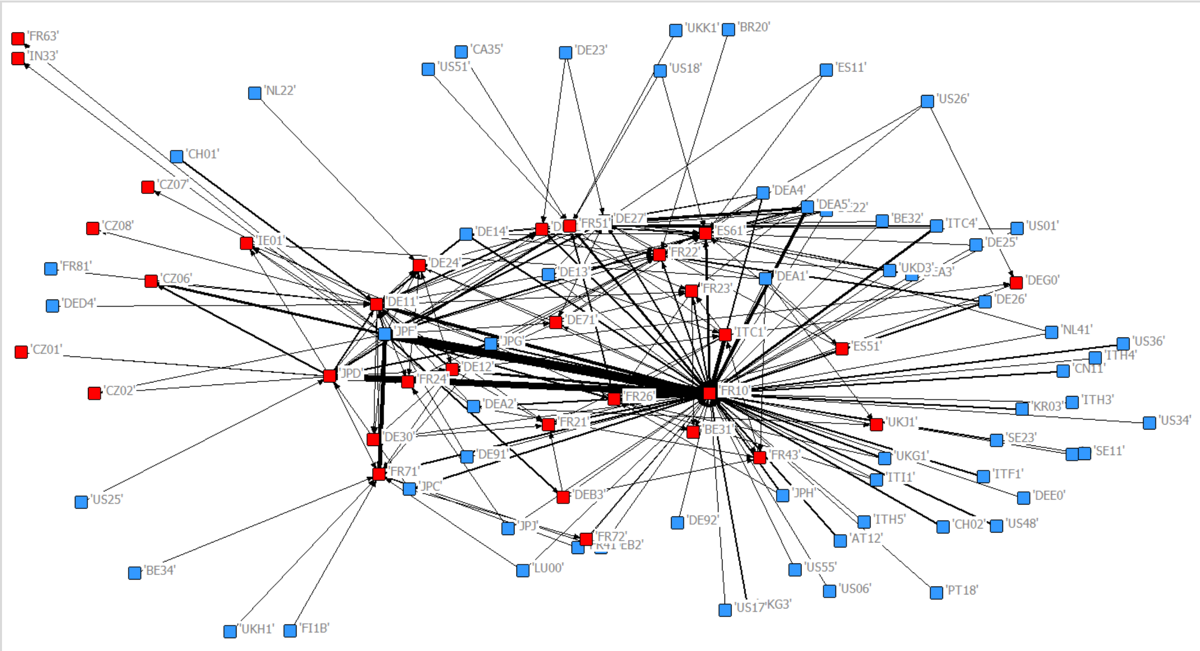
The US-based top R&D investor, General Electric, features important sourcing regions in the US, Europe, India (eg. Delhi, Rajasthan IN04), in Canada as well as the capital regions of Japan and Russia. Within Europe, three countries including the UK, France and Germany are home to the majority of regions where General Electric concentrates its technological knowledge generation activities (location of citing patents). Besides, non-European capital regions from Asia – Shanghai region (China) and Southern Kanto (Japan) – and the Mexican region Queretaro also come up as central for General Electric's regional global sourcing.

GENERAL ELECTRIC (HQ: United-States; ICB industry: General Industrials; Rank of centrality: 2nd)



France-based company Valeo concentrates its knowledge generation activities in France's regions (e.g. Ile de France, Bourgogne, Centre and Rhône-Alpes). Regions such as Darmstadt (Frankfurt's region), Karlsruhe, Oberfranken, Stuttgart and Berlin, make Germany the second most important territory for the knowledge generation activities of Valeo. Central non-EU knowledge poles include the capital city region of Japan, India's Tamil Nadu region and a few other European regions in Spain and the UK. The source regions for Valeo are concentrated in France and Germany, but also extend to a greater number of European and international regions, mainly located in Japan and US.

VALEO (HQ: France; ICB industry: Automobiles & Parts; Rank of centrality: 3rd)



V. Conclusion

Our analysis contributes to the literature on network centrality as a relevant approach to assess the involvement or contribution of a specific node or actor to the cohesiveness of the network. On the one hand, it provides complementary tools to assess the layers' contribution to the nodes centrality, allowing regions to understand which actors/fields are central for their technological development or position in a given technological space. On the other hand, applying network centrality approach to large R&D-driven and well-connected global firms can provide relevant bases for regional or local actors – universities, research centres, firms – in order to identify global pipelines and knowledge sources.

The empirical observations confirm important prior findings in terms of regional, national and international concentration, complexity and regional hierarchy in the geography of corporate knowledge flows across world regions (here proxy by the patent citations to prior patents). The study shows that it is also the case for the knowledge flows initiated by large R&D-driven firms. Besides, our analysis reveals the most central firms appear more geographically diversified than what could be expected from the hierarchy of most central territories. This suggests that, while every region may not attract the most globally connected firms, each region can indeed have a role in the global development of new technologies. Home-based firms clearly drive the centrality of home regions on the international scene. However, the results indicate that this pattern is less pronounced in Europe than in Asia, suggesting a greater internationalization of Europe-based top R&D investors.

While keeping in mind the limitations of the data used in this article, it is also important to underline the opportunities offered by the patent citations data. The explorations have shown that relevant insights on the structural properties of interregional knowledge networks, especially on the influence or contribution of specific actors to their cohesion, may be put forward.

Finally, although additional dynamic analyses are needed to provide sound evidence for policy, the study does offer a tool for regional comparisons in the context of global knowledge and innovation networks. Doing so, it can assist regions, for instance, to better benchmark themselves in a given technological space and to identify potential partner or competing regions with closer (or different) technological roles or sets of innovation related activities. In the EU Cohesion policy context, a better understanding of how (actors from) different regions connect through these large firms' networks is indeed a particularly valuable knowledge. The related evidence may be exploited in order to foster the inter-regional innovation networks and the participation of EU regions into the global innovation networks, often led by large and well-connected R&D-investing firms.

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<u>Annex 1.</u> Country coverage

Countries (ISO codes 2-digit)	**Number of firms**	**Countries (ISO codes 2-digit)**	**Number of firms**
United States (US)	268	Ireland (IE)	5
Japan (JP)	234	Norway (NO)	5
Germany (DE)	107	Australia (AU)	4
France (FR)	57	Cayman Islands (KY)	4
United Kingdom (UK)	46	Bermuda (BM)	3
Switzerland (CH)	37	Brazil (BR)	2
Taiwan (TW)	35	Hong Kong (HK)	2
Korea, Republic of (KR)	28	Curacao (CW)	1
Sweden (SE)	24	Hungary (HU)	1
Netherlands (NL)	22	Iceland (IS)	1
Italy (IT)	18	Liechtenstein (LI)	1
Finland (FI)	15	Luxembourg (LU)	1
Denmark (DK)	12	Mexico (MX)	1
India (IN)	12	Malaysia (MY)	1
Austria (AT)	11	Saudi Arabia (SA)	1
China (CN)	11	Singapore (SG)	1
Spain (ES)	11	Thailand (TH)	1
Belgium (BE)	8	Turkey (TU)	1
Israel (IL)	7	South Africa (ZA)	1
Canada (CA)	6	***Total***	***1006***

Annex 2. Names and codes of NUTS2 regions included in the analysis

AUSTRALIA (AU): NEW SOUTH WALES (AU1), VICTORIA (AU2), QUEENSLAND (AU3), SOUTH AUSTRALIA (AU4), AUSTRALIAN CAPITAL TERRITORY (AU8), WESTERN AUSTRALIA (AU5), TASMANIA (AU6), NORTHERN TERRITORY (AU7)

AUSTRIA (AT): BURGENLAND (AT11), NIEDERÃ–STERREICH (AT12), WIEN (AT13), KARNTEN (AT21), STEIERMARK (AT22), OBERÃ–STERREICH (AT31), SALZBURG (AT32), Tirol (AT33), VORARLBERG (AT34)

BRAZIL (BR): AMAZONAS (BR03), BAHIA (BR09), CEARA (BR10), PERNAMBUCO (BR13), RIO GRANDE DO NORTE (BR15), ESPIRITO SANTO (BR17), MINAS GERAIS (BR18), RIO DE JANEIRO (BR19), SÃO PAULO (BR20), PARANA (BR21), RIO GRANDE DO SUL (BR22), SANTA CATARINA (BR23), DISTRITO FEDERAL (BR24), GOIÃS (BR25)

BELGIUM (BE): BRUSSELS HOOFDSTEDELIJK GEWEST (BE10), PROV. ANTWERPEN (BE21), PROV. LIMBURG (B) (BE22), PROV. OOST-VLAANDEREN (BE23), PROV. VLAAMS-BRABANT (BE24), PROV. WEST-VLAANDEREN (BE25), PROV. BRABANT WALLON (BE31), PROV. HAINAUT (BE32), PROV. LIEGE (BE33), PROV. LUXEMBOURG (BE34), PROV. NAMUR (BE35)

BULGARIA (BG): SEVEREN TSENTRALEN BG32, SEVEROIZTOCHEN (BG33), YUGOZAPADEN (BG41)

CANADA (CA): NEW FOUNDLAND (CA10), NOVA SCOTIA (CA12), NEW BRUNSWICK (CA13), QUEBEC (CA24), ONTARIO (CA35), MANITOBA (CA46), SASKATCHEWAN (CA47), ALBERTA (CA48), BRITISH COLUMBIA (CA59)

CHILE (CL): VALPARAÍSO (CL05), BÍO BÍO (CL08), LOS LAGOS (CL10), SANTIAGO (CL13)

CHINA (CN): BEIJING (CN01), TIANJIN (CN02), HEBEI (CN03), SHANXI (CN04), INNER MONGOLIA (CN05), LIAONING (CN06), JILIN (CN07), HEILONGJIANG (CN08), SHANGHAI (CN09), JIANGSU (CN10), ZHEJIANG (CN11), ANHUI (CN12), FUJIAN (CN13), JIANGXI (CN14), SHANDONG (CN15), HENAN (CN16), HUBEI (CN17), HUNAN (CN18), GUANGDONG (CN19), GUANGXI (CN20), CHONGQING (CN22), SICHUAN (CN23), GUIZHOU (CN24), SHAANXI (CN27), GANSU (CN28), HONG KONG (CN32), TAIWAN (CN34)

CROATIA (HR): KONTINENTALNA HRVATSKA (HR04), JADRANSKA HRVATSKA (HR03)

CYPRUS (CY): KYPROS / KIBRIS (CY00)

CZECH REPUBLIC (CZ): PRAHA (CZ01), STREDNI CECHY (CZ02), JIHOZAPAD (CZ03), SEVEROZAPAD (CZ04), SEVEROVYCHOD (CZ05), JIHOVYCHOD (CZ06), STREDNI MORAVA (CZ07), MORAVSKOSLEZSKO (CZ08)

DENMARK (DK): HOVEDSTADEN (DK01), SJAELLAND (DK02), SYDDANMARK (DK03), MIDTJYLLAND (DK04), NORDJYLLAND (DK05)

ESTONIA (EE): EESTI (EE00)

FRANCE (FR): ILE DE FRANCE (FR10), CHAMPAGNE-ARDENNE (FR21), PICARDIE (FR22), HAUTE-NORMANDIE (FR23), CENTRE (FR24), BASSE-NORMANDIE (FR25), BOURGOGNE (FR26), NORD-PAS-DE-CALAIS (FR30), LORRAINE (FR41), ALSACE (FR42), FRANCHE-COMTE (FR43), PAYS DE LA LOIRE (FR51), BRETAGNE (FR52), POITOU-CHARENTES (FR53), AQUITAINE (FR61), MIDI-PYRENEES (FR62), LIMOUSIN (FR63), RHONE-ALPES (FR71), AUVERGNE (FR72), LANGUEDOC-ROUSSILLON (FR81), PROVENCE-ALPES-CÔTE DAZUR (FR82) , CORSE (FR83), GUADELOUPE (FR91), MARTINIQUE (FR92), GUYANE (FR93), REUNION (FR94)

FINLAND (FI): LÄNSI-SUOMI (FI19), HELSINKI-UUSIMAA (FI1B), ETELÄ SUOMI (FI1C), POHJOIS-JA ITÄ SUOMI (FI1D), ALAND (FI20)

GERMANY (DE): STUTTGART (DE11), KARLSRUHE (DE12), FREIBURG (DE13), TUBINGEN (DE14), OBERBAYERN (DE21), NIEDERBAYERN (DE22), OBERPFALZ (DE23), OBERFRANKEN (DE24), MITTELFRANKEN (DE25), UNTERFRANKEN (DE26), SCHWABEN (DE27), BERLIN (DE30), BRANDENBURG (DE40), BREMEN (DE50), HAMBURG (DE60), DARMSTADT (DE71), GIEßEN (DE72), KASSEL (DE73), MECKLENBURG-VORPOMMERN (DE80), BRAUNSCHWEIG (DE91), HANNOVER (DE92), LUNEBURG (DE93), WESER-SEM (DE94), DUSSELDORF (DEA1), KOLN (DEA2), MUNSTER (DEA3), DETMOLD (DEA4), ARNSBERG (DEA5), KOBLENZ (DEB1), TRIER (DEB2), RHEINHESSEN-PFALZ (DEB3), SAARLAND (DEC0), DRESDEN (DED2), CHEMNITZ (DED4), LEIPZIG (DED5), SACHSEN-ANHALT (DEE0), SCHLESWIG-HOLSTEIN (DEF0), THURINGEN (DEG0)

GREECE (EL): KENTRIKI MAKEDONIA (EL12), DYTIKI ELLADA (EL23), STEREA ELLADA (EL24), PELOPONNISOS (EL25), ATTIKI (EL30), KRITI (EL43)

HUNGARY (HU): KOZEP-MAGYARORSZAG (HU10), KOZEP-DUNANTUL (HU21), NYUGAT-DUNANTUL (HU22), DEL-DUNANTUL (HU23), ESZAK-MAGYARORSZAG (HU31), ESZAK-ALFOLD (HU32), DEL-ALFOLD (HU33)

INDIA (IN): JAMMU AND KASHMIR (IN01), HIMACHAL PRADESH (IN02), NATIONAL CAPITAL TERRITORY OF DELHI (IN03), RAJASTHAN (IN04), UTTAR PRADESH (IN05), ASSAM (IN10), WEST BENGAL (IN11), GUJARAT (IN12), MAHARASHTRA (IN14), LAKSHADWEEP (IN16), KERALA (IN17), PUNJAB (IN18), CHANDIGARH (IN19), HARYANA (IN20), UTTARAKHAND (IN21), BIHAR (IN22), JHARKHAND (IN23), ORISSA (IN27), MADHYA PRADESH (IN28), ANDHRA PRADESH (IN30), KARNATAKA (IN31), GOA (IN32), TAMIL NADU (IN33), PUDUCHERRY (IN34)

IRELAND (IE): BORDER, MIDLAND AND WESTERN (IE01), SOUTHERN AND EASTERN (IE02)

ISLAND (IS): CAPITAL REGION (IS01), OTHER REGIONS (IS02)

ISRAEL (IL): JERUSALEM DISTRICT (IL01), NORTHERN DISTRICT (IL02), HAIFA DISTRICT (IL03), CENTRAL DISTRICT (IL04), TEL AVIV DISTRICT (IL05), SOUTHERN DISTRICT (IL06)

ITALY (IT): PIEMONTE (ITC1), VALLE DAOSTA (ITC2), LIGURIA (ITC3), LOMBARDIA (ITC4), ABRUZZO (ITF1), MOLISE (ITF2), CAMPANIA (ITF3), PUGLIA (ITF4), BASILICATA (ITF5), CALABRIA (ITF6), SICILIA (ITG1), SARDEGNA (ITG2), PROV. AUTONOMA DI BOLZANO/BOZEN (ITH1), PROV. AUTONOMA DI TRENTO (ITH2), VENETO (ITH3), FRIULI-VENEZIA GIULIA (ITH4), EMILIA-ROMAGNA (ITH5), TOSCANA (ITI1), UMBRIA (ITI2), MARCHE (ITI3), LAZIO (ITI4)

JAPAN (JP): HOKKAIDO (JPA), TOHOKU (JPB), NORTHERN-KANTO, KOSHIN (JPC), SOUTHERN-KANTO (JPD), HOKURIKU(JPE), TOUKAI (JPF), KINKI (JPG), CHUGOKU (JPH), SHIKOKU (JPI), KYUSHU, OKINAWA (JPJ)

KOREA, REPUBLIC OF (KR): CAPITAL REGION (KR01), GYEONGNAM REGION (KR02), GYEONBUK REGION (KR03), JEOLLA REGION (KR04), CHUNGCHEONG REGION (KR05), GANGWON REGION (KR06), JEJU (KR07)
LATVIA (LV): LATVIJA (LV00)

LITHUANIA (LT): LIETUVA (LT00)

LUXEMBOURG (LU): LUXEMBOURG (LU00)

MALTA (MT): MALTA (MT00)

MEXICO (ME): BAJA CALIFORNIA NORTE (ME02), COAHUILA (ME05), CHIHUAHUA (ME08), DISTRITO FEDERAL (ME09), DURANGO (ME10), GUANAJUATO (ME11), HIDALGO (ME13), JALISCO (ME14), MEXICO (ME15), NUEVO LEON (ME19), PUEBLA (ME21), QUERETARO (ME22), QUINTANA ROO (ME23), TAMAULIPAS (ME28), TLAXCALA (ME29), VERACRUZ (ME30), YUCATAN (ME31)

NEW ZELAND (NZ): NORTH ISLAND (NZ01), SOUTH ISLAND (NZ02)

NORWAY (NO): OSLO OG AKERSHUS (NO01), HEDMARK OG OPPLAND (NO02), SØR-ØSTLANDET (NO03), AGDER OG ROGALAND (NO04), VESTLANDET (NO05), TRÃ˜NDELAG (NO06), NORD-NORGE (NO07)

POLAND (PL): LODZKIE (PL11), MAZOWIECKIE (PL12), MALOPOLSKIE (PL21), SLASKIE (PL22), LUBELSKIE (PL31), PODKARPACKIE (PL32), PODLASKIE (PL34), WIELKOPOLSKIE (PL41), ZACHODNIOPOMORSKIE (PL42), LUBUSKIE (PL43), DOLNOSLASKIE (PL51), OPOLSKIE (PL52), KUJAWSKO-POMORSKIE (PL61), WARMINSKO-MAZURSKIE (PL62), POMORSKIE (PL63)

PORTUGAL (PT): NORTE (PT11), CENTRO (PT16), LISBOA (PT17), ALENTEJO (PT18)

ROMANIA (RO): NORD-VEST (RO11), CENTRU (RO12), NORD-EST (RO21), SUD-MUNTENIA (RO31), BUCURESTI-ILFOV (RO32), SUD-VEST OLTENIA (RO41), VEST (RO42)

RUSSIA (RU): BRYANSK OBLAST (RU02), VORONEZH OBLAST (RU04), KALUGA OBLAST (RU06), KURSK OBLAST (RU08), LIPETSK OBLAST (RU09), MOSCOW OBLAST (RU10), RYAZAN OBLAST (RU12), TULA OBLAST (RU16), CITY OF MOSCOW (RU18), KOMI REPUBLIC (RU20), VOLOGDA OBLAST (RU23), PSKOV OBLAST (RU28), FEDERAL CITY OF SAINT PETERSBURG (RU29), REPUBLIC OF DAGESTAN (RU31), VOLGOGRAD OBLAST (RU41), ROSTOV OBLAST (RU42), REPUBLIC OF TATARSTAN (RU46), UDMURT REPUBLIC (RU47), PERM KRAI (RU49), NIZHNY NOVGOROD OBLAST (RU51), SAMARA OBLAST (RU54), SVERDLOVSK OBLAST (RU58), CHELYABINSK OBLAST (RU62), ALTAI KRAI (RU67), KRASNOYARSK KRAI (RU68), NOVOSIBIRSK OBLAST (RU71), TOMSK OBLAST (RU73), KHABAROVSK KRAI (RU77)

SLOVAKIA (SK): BRATISLAVSKY KRAJ (SK01), ZAPADNE SLOVENSKO (SK02), STREDNE SLOVENSKO (SK03), VYCHODNE SLOVENSKO (SK04)

SLOVENIA (SI): VZHODNA SLOVENIJA (SI01), ZAHODNA SLOVENIJA (SI02)

SOUTH AFRICA (ZA): EASTERN CAPE (ZA01), FREE STATE (ZA02), GAUTENG (ZA03), KWAZULU-NATAL (ZA04), NORTHERN CAPE (ZA07), WESTERN CAPE (ZA09)

SPAIN (ES): GALICIA (ES11), PRINCIPADO DE ASTURIAS (ES12), CANTABRIA (ES13), PAIS VASCO (ES21), COMUNIDAD FORAL DE NAVARRA (ES22), LA RIOJA (ES23), ARAGON (ES24), COMUNIDAD DE MADRID (ES30), CASTILLA Y LEON (ES41), CASTILLA-LA MANCHA (ES42), CATALUNA (ES51), COMUNIDAD VALENCIANA (ES52), ANDALUCIA (ES61), REGION DE MURCIA (ES62), CANARIAS (ES70)

SWEDEN (SE): STOCKHOLM (SE11), ÖSTRA MELLANSVERIGE (SE12), SMÅLAND MED ÖARNA (SE21), SYDSVERIGE (SE22), VÄSTSVERIGE (SE23), NORRA MELLANSVERIGE (SE31), MELLERSTA NORRLAND (SE32), ÖVRE NORRLAND (SE33)

SWITZERLAND (CH): LEMANIC REGION (CH01), ESPACE MITTELLAND (CH02), NORDWESTSCHWEIZ (CH03), ZURICH (CH04), OSTSCHWEIZ (CH05), ZENTRALSCHWEIZ (CH06), TICINO (CH07)

THE NETHERLANDS (NL): GRONINGEN (NL11), FRIESLAND (NL12), DRENTHE (NL13), OVERIJSSEL (NL21), GELDERLAND (NL22), FLEVOLAND (NL23), UTRECHT(NL31), NOORD-HOLLAND (NL32), ZUID-HOLLAND (NL33), ZEELAND (NL34), NOORD-BRABANT (NL41), LIMBURG (NL42)

TURKEY (TR): ISTANBUL (TR10), TEKIRDAG (TR21), IZMIR (TR31), MANISA (TR33), BURSA (TR41), KOCAELI (TR42), ANKARA (TR51), ADANA (TR62), HATAY (TR63), KASTAMONU (TR82), SAMSUN (TR83), TRABZON (TR90), GAZIANTEP (TRC1)

UNITED KINGDOM (UK): TEES VALLEY AND DURHAM (UKC1), NORTHUMBERLAND AND TYNE AND WEAR (UKC2), CUMBRIA (UKD1), GREATER MANCHESTER (UKD3), LANCASHIRE (UKD4), CHESHIRE (UKD6), MERSEYSIDE (UKD7), EAST YORKSHIRE AND NORTHERN LINCOLNSHIRE (UKE1), NORTH YORKSHIRE (UKE2), SOUTH YORKSHIRE (UKE3), WEST YORKSHIRE (UKE4), DERBYSHIRE AND NOTTINGHAMSHIRE (UKF1), LEICESTERSHIRE, RUTLAND AND

NORTHAMPTONSHIRE (UKF2), LINCOLNSHIRE (UKF3), HEREFORDSHIRE, WORCESTERSHIRE AND WARWICKSHIRE (UKG1), SHROPSHIRE AND STAFFORDSHIRE (UKG2), WEST MIDLANDS (UKG3), EAST ANGLIA (UKH1), BEDFORDSHIRE AND HERTFORDSHIRE (UKH2), ESSEX (UKH3), INNER LONDON (UKI1), OUTER LONDON (UKI2), BERKSHIRE, BUCKINGHAMSHIRE AND OXFORDSHIRE (UKJ1), SURREY, EAST AND WEST SUSSEX (UKJ2), HAMPSHIRE AND ISLE OF WIGHT (UKJ3), KENT (UKJ4), GLOUCESTERSHIRE, WILTSHIRE AND BRISTOL/BATH AREA (UKK1), DORSET AND SOMERSET (UKK2), CORNWALL AND ISLES OF SCILLY (UKK3), DEVON (UKK4), WEST WALES AND THE VALLEYS (UKL1), EAST WALES (UKL2), EASTERN SCOTLAND (UKM2), SOUTH WESTERN SCOTLAND (UKM3), NORTH EASTERN SCOTLAND (UKM5), HIGHLANDS AND ISLANDS (UKM6), NORTHERN IRELAND (UKN0)

UNITED STATES (US): ALABAMA (US01), ALASKA (US02), ARIZONA (US04), ARKANSAS (US05), CALIFORNIA (US06), COLORADO (US08), CONNECTICUT (US09), DELAWARE (US10), DISTRICT OF COLUMBIA (US11), FLORIDA (US12), GEORGIA (US13), HAWAII (US15), IDAHO (US16), ILLINOIS (US17), INDIANA (US18), IOWA (US19), KANSAS (US20), KENTUCKY (US21), LOUISIANA (US22), MAINE (US23), MARYLAND (US24), MASSACHUSETTS (US25), MICHIGAN (US26), MINNESOTA (US27), MISSISSIPPI (US28), MISSOURI (US29), MONTANA (US30), NEBRASKA (US31), NEVADA (US32), NEW HAMPSHIRE (US33), NEW JERSEY (US34), NEW MEXICO (US35), NEW YORK (US36), NORTH CAROLINA(US37), NORTH DAKOTA (US38), OHIO (US39), OKLAHOMA (US40), OREGON (US41), PENNSYLVANIA (US42), RHODE ISLAND (US44), SOUTH CAROLINA (US45), SOUTH DAKOTA (US46), TENNESSEE (US47), TEXAS (US48), UTAH (US49), VERMONT (US50), VIRGINIA (US51), WASHINGTON (US53), WEST VIRGINIA (US54), WISCONSIN (US55), WYOMING (US56)

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