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The Geography and Co-location of European Technology-specific Co-inventorship Networks [†]

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Abstract

This paper contributes with empirical findings to European co-inventorship location and geographical coincidence of co-patenting networks. Based on EPO co-patenting information for the reference period 2000-2004, we analyze the spatial configuration of 44 technology-specific co-inventorship networks. European co-inventorship (co-patenting) activity is spatially linked to 1259 European NUTS3 units (EU25+CH+NO) and their NUTS1 regions by inventor location. We extract 7.135.117 EPO co-patenting linkages from our own relational database that makes use of the OECD RegPAT (2009) files. The matching between International Patent Classification (IPC) subclasses and 44 technology fields is based on the ISI-SPRU-OST-concordance. We confirm the hypothesis that the 44 co-inventorship networks differ in their overall size (nodes, linkages, self-loops) and that they are dominated by similar groupings of regions. The paper offers statistical evidence for the presence of highly localized European co-inventorship networks for all 44 technology fields, as the majority of linkages between NUTS3 units (counties and districts) are within the same NUTS1 regions. Accordingly, our findings help to understand general presence of positive spatial autocorrelation in regional patent data. Our analysis explicitly accounts for different network centrality measures (betweenness, degree, eigenvector). Spearman rank correlation coefficients for all 44 technology fields confirm that most co-patenting networks co-locate in those regions that are central in several technology-specific co-patenting networks. These findings support the hypothesis that leading European regions are indeed multi-field network nodes and that most research collaboration is taking place in dense co-patenting networks.

Keywords: co-patenting, co-inventorship, networks, linkages, co-location, RegPAT

JEL classification: C8, O31, O33, R12

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1 Introduction

Geographical economics, economic geography proper and innovation system adherents have an established tradition in studying spatial clustering and agglomeration economies with respect to the benefits of geographical proximity for inventorship and innovation what is often labeled '*Marshallian externalities of the third kind*': agents located close to relevant knowledge stocks are able to innovate faster than agents far away, since they benefit from spatially bounded externalities.¹ Particularly high-tech industries are assigned to show strong tendencies to cluster in space as shown by Feldman (1994), Audretsch and Feldman (1996, 1999) and Scherngell (2007). There is a wide consensus that localized knowledge spillovers and knowledge flows constitute an important working channel for knowledge transfer and that these factors have a positive impact on innovation, per capita growth and employment (Breschi and Lissoni, 2001, 2003, 2009; Bottazzi and Peri 2003).² In this respect, the analysis of information included in patent data is considered to be one of the most appropriate and established, directly available and historically reliable instruments for exploring the performance and dynamics of sectoral and regional innovation systems. According to Griliches (1990, 1661), "*[i]n this desert of data, patent statistics loom up as a mirage of wonderful plenitude and objectivity.*" No other STI-indicator can be traced back over such a comparatively long time period as patent applications or information of granted patents (Griliches, 1981, 1990, 1992; Jaffe, 1989; Jaffe et al., 1993). Additionally, the information can be disaggregated to low spatial levels, e.g. cities, counties, districts, provinces, regions; and perhaps most important, the information of inventorship can be allocated to individual economic units (individuals, firms). The information is also precise and accurate by means of an identification of the timing of the invention (priority application, priority date). However, there is also accepted criticism that patent data are only a very imperfect measure of innovative activities that have several limitations. First, the range of patentable inventions constitutes only a subset of all possible R&D outcomes. Second, patenting is in most cases a strategic decision of firms and thus not all inventions are actually patented by agents even though inventions would satisfy the criteria for patentability. Third, many scientific advances devoid of immediate applicability and little incremental technological improvements might not be patentable. Fourth, inventions vary tremendously in their economic value (Griliches, 1992; Hoekman et al., 2008).

A strong motivation for exploring European co-inventorship networks from relational patent data comes from the fact that spatial data in general show strong spatial autocor-

¹ The New Economic Geography tradition is explicitly focusing on pecuniary externalities derived from internal and external economies that manifest in scale economies at the firm level and additional pecuniary externalities from co-location that foster centripetal forces and cumulative causation at the industry or regional level. Knowledge spillovers are only important in New Economic Geography Growth Models (NEGG) that have been pushed forward by Martin and Ottaviano (1999), Baldwin and Forslid (2000), Baldwin et al. (2001), Baldwin and Martin (2004) and Bottazzi and Dindo (2008).

² see also Moreno-Serrano et al. (2005), Greunz (2003, 2004, 2005), Crescenzi et al. (2007), Usai (2008), Hoekman et al. (2008), Ponds et al. (2010).

relation, which is a severe issue for econometric models (Fotheringham et al., 2002; Anselin, 2007; Hauser et al., 2008). Interestingly, spatial autocorrelation of STI indices seems to be not that strong for US regions compared to Europe (Crescenzi et al., 2007; Andersson and Grasjo, 2009) what would support the hypothesis that inventorship in Europe is much more determined by spatial interaction than in the USA. In this respect, the paper offers a clear hypothesis and explanation, why knowledge production functions (especially in Europe) are always characterized by significant positive global and local spatial autocorrelation, which generally needs econometric treatment in terms of spatially weighted regressors. However, treatment of global spatial autocorrelation only accounts for spatial dependence, whereas spatial heterogeneity (regimes) could still represent an econometric problem. The paper challenges both spatial dependence and heterogeneity by explicitly approaching co-inventorship network structures within and between 1259 European NUTS3 units (counties and districts) and their respective NUTS1 aggregates (176 regions). We will show that the analysis of technology-specific EPO co-patenting networks is a key approach in understanding the spatial context of co-inventorship and in explaining spatial dependence and heterogeneity.

Another motivation for this co-inventorship network analysis at the European level of counties, districts and regions is the fact that complex inventorship and co-inventorship networks represent the counterpart of industry agglomerations and innovation clusters. The approach is fruitful, as it sheds light on the inter- and intra-regional connectedness of regions in terms of co-inventorship linkages and network centrality. In addition, we can focus on innovation centers, the 'core-units' of the networks, but also on the most peripheral nodes (vertices) by means of linkages. From a core-periphery perspective, it is then essential to depict the *hub-and-spoke* structure of technology fields. Some regions represent weak and de-centralized nodes, whereas other spatial units are obtaining a *gatekeeping position* in certain technology fields. Additionally, some regions or counties could represent *multi-technology hubs* due to their co-inventorship strength in several technology fields. Accordingly, this research paper tries to find empirical evidence for the following open research questions: *(i) Do technology fields differ in their overall network size?; (ii) Which are the most connected regions in EPO co-patenting networks? (iii) Which regions represent the most essential industry leaders in a specific technology field? (iv) Which regions represent crucial within- and between-network bridges? (v) Which regions are the most isolated ones in European technology specific co-patenting networks?; (vi) Are European regions characterized by a diversified technology base and multi-technology network hubs?*

As a consequence, the paper aims contributing to a better understanding of the spatial structure of European technology-specific co-inventorship networks in three respects: *(i) depicting the global configuration of co-inventorship networks for 43 technology fields; (ii) describing the structure of co-inventorship networks by means of technological and spatial proximity at the county level (NUTS3) and the level of regions (NUTS1); (iii) contributing with an alternative research methodology to the recent debate; and (iv) contributing with new data generated from OECD RegPAT (2009) files.* Based on our own relational database,

inventor locations are assigned to European counties and regions by inventor address as proposed by Maraut et al. (2008). We utilize the inventor location information for exploring co-inventorship networks for different technology fields.

The paper is structured as follows. Section 2 reviews the literature on knowledge flows, spillovers and the spatial pattern of inventorship interaction. Section 3 describes the underlying database structure and the data extraction process. Section 4 then highlights our research methodology. In section 5, we describe the empirical findings from our co-inventorship network analysis. Finally, section 6 concludes.

2 Theoretical and Empirical Review

Patent data are widely used in the economic literature in order to measure knowledge spillover and other spatial externalities, e.g. Griliches (1979), Griliches (1990), Griliches (1991), Griliches (1992); Griliches and Pakes (1980b); Jaffe (1989); Jaffe et al. (1993); Jaffe and Trajtenberg (1999)). Such spillover do, in contrast to the criticism by Krugman (1991) and Fujita and Krugman (2003), leave a paper trail and seem to be highly localized (Jaffe et al., 1993, Jaffe et al., 2002). Jaffe (1989) finds a significant and positive correlation between university R&D and neighbouring firms patenting activity, which seems to confirm the presence of knowledge externalities. Griliches (1998) concludes that *"[t]he more difficult to measure and the possibly more interesting and pervasive aspect of R&D externalities is the impact of the discovered ideas on the productivity of the research endeavour of others."* (Griliches, 1998, 252) Unfortunately, it seems rather difficult, perhaps impossible, to separate pure knowledge spillover from pecuniary externalities in a spatial context, although several authors have contributed with seminal approaches that make use of patent data (Jaffe, 1989; Jaffe et al., 1993; Breschi and Lissoni, 2003, 2006, 2009). In this respect, it is a first attempt to adapt the knowledge production function approach of Griliches (1979) in a way which takes geography explicitly into account. Although most studies on KPF refer explicitly to Griliches' analysis and research methodologies, most studies use aggregated spatial data instead of firm-level data. Additionally, most studies do, in opposition to Griliches (1979) introduce additional variables besides traditional production factors (Autant-Bernard and Massard, 2005). The main research aspect of the KPF studies is related to *(i) the type of externality and transfer channels, (ii) its spatial range, and (iii) its strength and decay effects on employment, productivity, innovative activity, and also patenting activity of neighboring units.* The estimation of European inter- and intra-regional knowledge spillover, besides concentration and specialization measures, within KPF analysis mainly started with Bottazzi and Peri (2000); a recent contribution is Usai (2008).³ In this respect, regional innovation data

³ Further seminal contributions that address spatial lagging regressors of innovative activity are Bottazzi and Peri (2003), Moreno et al. (2005b), Moreno et al. (2005a), Greunz (2003a), Greunz (2004), Greunz (2005), Crescenzi and Rodriguez-Pose (2006), Maggioni et al. (2007), Fritsch and Slavtchev (2007), Crescenzi et al. (2007), Bottazzi and Peri (2008), and Andersson and Gråsjö (2009). Christ (2009) offers a detailed META study on the KPF approach. The EU research lag compared with the US is mainly

generally show significant evidence for spatial (auto-)correlation and unequal distribution of innovation potentialities across space. However, most studies do control for the econometric issues of spatial dependence by applying global instruments (spatial autoregressive and cross-regressive models), which means that spatial dependence is treated for the whole sample of observations by application of spatially weighted regressors generated from spatial weight matrices.⁴ Whereas spatial weight matrices, in general, are exogenous, the application of a social network weight matrix could exhibit the issue of potential endogeneity, as the geographical structure of collaborations (in our case co-inventorship activity) are likely to be related to spatial patterns of patenting. The usage of network data has the clear advantage that it builds upon a direct relation with the theoretical conceptualization of the structure of spatial dependence and not an *ad hoc* explanation of a spatial patterns (Anselin, 1988; Ponds et al., 2009). The econometric treatment of spatial dependence, however, partially ignores region-specific set-ups and heterogeneous spatial systems which are defined by differing functional (and spatial) boundaries what we call spatial heterogeneity (Fotheringham et al., 2002; Anselin, 2007).⁵ Such spatial heterogeneity exists if spatial processes are not global; the structure of the process being modeled is not spatially uniform within or across space (Fotheringham et al., 2002). In this respect, the analysis of network structures, opposed to spatial econometrics, has the clear advantage that it unveils the real structure of spatial interaction, not assuming an *ad hoc* spatial structure (Anselin, 1988; Ponds et al., 2009). As empirical research on the geographical dimension of these networks also stresses the importance of inter-regional and border-crossing collaborations (linkages), technology-specific networks are assumed to differ in their overall size and density (Breschi and Lissoni, 2001, 2003, 2006; Ponds et al., 2009). This is one hypothesis we are challenging.

Another established research approach for depicting and analyzing innovation networks and knowledge flows is to use patent citation data. This method is well-known in empirical analysis, especially for approaching knowledge spillover and inventor linkages as an alternative

based on spatially disaggregated data constraints. In this respect, Crescenzi et al. (2007) and Usai (2008) represent unique contributions as they explicitly compare spatial KPFs for Europe and the US or even for OECD regions.

⁴ If we do not want to estimate a pure auto-regressive mechanism (spatially lagging dependent variable), we can address spatial dependence via a cross-regressive global process. In this respect, the following equation includes neighboring region j 's inputs, which are now linked to region i 's innovative output via the application of a spatial weight parameter d_{ij} , derived from a spatial weight matrix.

$$\begin{aligned}
\log PAT_{i,t} = & \alpha_0 + \alpha_1 \log BusinR\&D_{i,t-T} + \alpha_2 \log PublR\&D_{i,t-T} + \alpha_3 \log UnivR\&D_{i,t-T} & (1) \\
& + \alpha_4 \log Density_{i,t-T} + \alpha_5 \log High - techManuf_{i,t-T} + \alpha_6 \log KnowlServ_{i,t-T} \\
& + \sum_{m=1}^n \alpha_m NationDummy_{i,t} + \sum_{q=1}^r \alpha_q RegionDummy_{i,t} + \gamma_1 d_{ij} \log BusinR\&D_{j,t-T} \\
& + \gamma_2 d_{ij} \log PublR\&D_{j,t-T} + \gamma_3 d_{ij} \log UnivR\&D_{j,t-T} + \gamma_4 d_{ij} \log KnowlServ_{j,t-T} + \varepsilon_{i,t}
\end{aligned}$$

⁵ Hauser et al. (2008) criticize recent KPF estimation by means of model misspecifications. They argue, in line with Crescenzi and Rodriguez-Pose (2006), that the incorporation of a social filter variable (political interest, friendship ties, trust, associational activity and technological and self improvement) would reduce spatial dependence.

to knowledge production function estimations (Breschi and Lissoni, 2006, 2009; Alcacer and Gittelman, 2004; Thompson and Fox-Kean, 2005; Fischer et al., 2005; Scherngell, 2007). The spatial range of citations within the selected sample of patent data is compared to a control group. However, localized knowledge flows, as measured by the patent citation approach, are not always *pure spillover* from non-market based social interactions, given that their carrier is a standard market transaction. Then, the contracting agents will make several efforts and the knowledge transfer happens at a certain price, not for free, what reduces the extent of being a pure spillover (Scitovsky, 1954; Döring and Schnellbach, 2006; Breschi and Lissoni, 2001, 2003, 2009). Research collaboration would then be considered as being a process of knowledge co-production, in which inputs are transformed into patent applications. In this respect, knowledge spillover could occur as a by-product of such collaborations. However, the citation approach can be misleading and biased due to the fact that a large fraction of citations are added by patent examiners of the EPO (and USPTO). Criscuolo and Verspagen (2008) show that the share of patents with all citations included by the inventor has been constantly declining (from 10% in 1985 to 5% in 2000), while the fraction of patents with all citations added by the examiner has been rather constant. Additionally, they show that the shares of all citations added by EPO examiners instead of inventors differ tremendously: in organic chemistry, for example, almost 15% (65%) of all citations are added by the inventor (examiner), while in information technology only 2% of all citations are added by the inventor (93% by examiner). However, their results clearly support the importance of spatial distance for EPO patent citations by inventors (Criscuolo and Verspagen, 2008). According to these results, we favor co-patenting network analysis over patent citation analysis.

Almeida and Kogut (1999) and Zucker et al. (1998) assume that the reason why knowledge flows are spatially bounded is based on the peculiarities of scientists and engineers labor markets, rather than in the way of communication within and between informal social networks (tacit knowledge debate). In addition, several studies show that *(i) co-inventorship networks and knowledge spillover are both highly concentrated in space* (Döring and Schnellbach, 2006); but it is also highlighted that *(ii) inter-regional and border-crossing collaborations and induced inventor linkages and technology-specific networks differ in their overall size and connectedness* as reported by Maggioni and Uberti (2006), Hoekman et al. (2008), Breschi and Lissoni (2009), Kroll (2009) and Ponds et al. (2009).

Collaborative knowledge production by co-inventorship networks have been studied mainly at the regional or national level for selected countries and small samples. Andersson and Ejermo (2002) and Ejermo and Karlsson (2004) analyze co-inventorship activity for Swedish regions based on patent data. Breschi and Lissoni (2006) analyze the probability of localized Italian inventor networks by means of mobility of scientists. As Breschi and Lissoni (2006) conclude: *"[i]t remains true, however, that many social networks dedicated to the production of knowledge as a club good are geographically bounded, since spatial proximity may help the network members to communicate more effectively and patrol each other's behaviour."* (Breschi and Lissoni, 2006, 9) They furthermore refer to club good characteristics noting that

"[s]pillovers from an active club member will reach distant fellow members with some delay or imprecision, and will possibly never reach outsiders. [...] To the extent that many networks are concentrated in space, co-localisation would appear as a significant determinant of access to spillovers." (Breschi and Lissoni, 2006, 8)

Ponds et al. (2009) present a network analysis for Dutch regions based on scientific publications. Hoekman et al. (2008) offer results of their European co-inventorship analysis with special focus on scientific (journal) publications (Web of Science), combined with EPO patent data. Maggioni et al. (2007) similarly analyze co-inventorship networks, however, only for six European countries at the regional level. Miguelez and Moreno (2010) similarly focus on research networks in Europe. All these studies provide first results that co-inventorship networks seem to be largely influenced by spatial distance. In following ideas of Breschi and Lissoni (2006, 2009), Miguelez et al. (2009) use regionalized PCT patent data (EURO PCT) for studying the mobility of highly-skilled individuals, which represents one possible mechanism of knowledge spillover. The authors hypothesize that knowledge flows are localized to the extent that inventors' mobility is also localized, what would explain the existence of strong spatial dependence in explanatory spatial data analysis (ESDA). In a similar way, Breschi and Lissoni (2009) argue that *"the most fundamental reason why geography matters in constraining the diffusion of knowledge is that mobile researchers are not likely to relocate in space, so that their co-invention network is also localized."* (Breschi and Lissoni, 2009, 1)⁶

The applied method in our paper reveals spatial interaction by means of co-inventorship due to the direct analysis of EPO co-patenting linkages in a technological and spatial dimension. In this respect, our paper analyzes knowledge flows between spatial units through research collaborations instead of pure technological spillovers. As a consequence, this analysis has to be recognized as a complementary approach to patent citation tracking studies. We also interpret this analysis as a complementary approach to econometric estimations in the (spatial) knowledge production function (KPF) tradition represented by Griliches and Pakes (1980a), Jaffe (1989) and colleagues.⁷

3 The Database

3.1 Structure and Mechanisms

The analysis in this paper is based upon OECD RegPAT data, June 2009 (Maraut et al., 2008). The RegPAT files have been implemented into a workable *mysql database* as

⁶ Further interesting studies in this respect are Maggioni and Uberti (2006), Maggioni and Uberti (2009), Maggioni et al. (2007), Kroll (2009), and Ponds et al. (2010).

⁷ see also Coe and Helpman (1995), Audretsch and Feldman (1996), Audretsch and Feldman (1999), Anselin (2000), Acs et al. (1997), Varga (2000), Acs et al. (2002), Bottazzi and Peri (2000), Bottazzi and Peri (2003), Bottazzi and Peri (2008), Greunz (2003b), Greunz (2003a), Greunz (2004), Greunz (2005), Moreno et al. (2005b), Moreno et al. (2005a), LeSage et al. (2007), Scherngell et al. (2007), Crescenzi et al. (2007), Crescenzi and Rodríguez-Pose (2008), Usai (2008), and Ponds et al. (2010). Christ (2009) offers a detailed review and META study of the KPF approach with explicit focus on spatial autocorrelation.

presented in table 1 in order to generate *relational data* from EPO patent information.

< table 1 about here >

The relational mySQL database can be based either upon Patent Corporation Treaty (PCT) patent data or EPO patent application data. This paper is exclusively related to the geography of European co-inventorship networks within and between European counties/districts and regions, which consequentially prefers EPO to PCT patent applications, due to an explicitly defined macro level (minimizing potential spatial bias). Table 2 summarizes the spatial structure.

< table 2 about here >

Our relational EPO patent database builds upon several interlinked data files, which include 1.829.807 EPO patent applications from 1977 until 2005 (by priority date). Based on that relational database (inventor address information) each inventor is assigned to a certain NUTS3 county and NUTS1 region. The actors are in general inventors, who's postal address, which is their work place location, can be used to determine their location in geographical space. However, the paper does consider co-inventorship networks of counties (NUTS3) and regions (NUTS1) rather than network of individuals, but maintaining that behind the spatial co-inventorship network lies the network of individuals. Furthermore, the spatial co-inventorship networks are weighted ones, meaning that a linkage between two different spatial units has a weight referring to the overall number of patents on which inventors of these two regions had worked together (co-inventorship). Consequently, we produce networks of counties (NUTS3) and regions (NUTS1) in which the intensity of *inter-regional relationships* (co-patenting collaborations) is reflected by the number of *co-invented EPO patent applications*. We utilize this information for exploring co-inventorship networks for different technology fields. The overall number of patents for the co-inventorship analysis between 1977-2005 with more than one inventor is 672.432. These patents are selected on the basis of *full counting*, meaning that each inventor pair (between-county linkage) is counted as an inter-regional co-inventorship linkage or research collaboration that ended with a patent application to the EPO. We do not count patents that exclusively contain within-county linkages (only within NUTS3) as we are mainly interested in *inter-regional collaboration* at the county level (between NUTS3) and regional level (NUTS1). The resulting inventor pairs (linkages) of each patent application (unique ID) have to contain always at least two inventors from different NUTS3 units. Accordingly, we extract four different types of linkages: (i) *within-NUTS3 linkages* if there is at least a third additional inventor from another NUTS3 entity; (ii) *between-NUTS3 linkages*; (iii) *within-NUTS1 linkages* and (iv) *between-NUTS1 linkages*. Figure 1 highlights the data extraction process for the co-inventorship network analysis in detail. The extracted inventor pairs of each patent application (unique ID) do always contain at least two inventors from different counties. The overall number of extracted linkages for the period 2000-2004 is 7.135.117.

< figure 1 about here >

3.2 The Spatial Level

A serious problem in geographical economics and the geography of innovation literature is the definition and usage of spatial units. For modeling inventor networks, we need at least two entities that are in general called a place, a region or county. However, the difficulty with this concept is rather unnoticed and it seems that people have to suffer from the same theoretical vagueness with the '*concept of the region*' as with the '*concept of the industry*', which essentially depends on statistical classifications. Both concepts resemble some intermediate and flexible levels of aggregation and are thus not easy to define. Finally, the aggregation of places to a certain region depends essentially on the underlying research question and empirical application. The selection of borders mainly depends on the existence of spatial dependence, what could be an indication for functional regions. Accordingly, the aggregation issue is highly fuzzy and crucial in applied research. Admittedly, the usage of administrative entities such as the *European Nomenclature of Territorial Units for Statistics* (NUTS) simplifies the issue of functional spatial boundaries of regional systems.⁸ However, for the co-inventorship network analysis of large patent databases, the NUTS3 level is the most detailed and statistically useful regionalization level available for OECD countries and European member states; it also simplifies comparison with other studies. We simplify by interpreting NUTS3 units as *counties or districts*, although the regional size of the units vary to some extent (150.000-800.000 citizens). However, for the co-inventorship network analysis, the NUTS3 level is the smallest possible regionalization level for large patent databases. We therefore take the usual NUTS3 units as the general geographical concept for building co-inventorship linkages. For addressing potential *labor market effects*, such as commuting of inventors, we also aggregate the extracted co-inventorship linkages to the NUTS1 level. As a result, some linkages that appear between NUTS3 units (districts) but within the same regional NUTS1 unit are counted as a *self loop*. The underlying relational database extraction in this paper thus focuses on 1259 NUTS3 units and 176 NUTS1 regions as highlighted in table 2 and figure 14. The analyzed sample of 1259 NUTS3 units is formed by 1214 NUTS3 counties/districts of the EU25 member states and additional 45 NUTS3 units from Norway (19 NUTS3) and Switzerland (26 NUTS3). We include Switzerland (CH) and Norway (NO) to avoid *black holes* in the network structure. However, we exclude Croatia (HR), Romania (RO) and Liechtenstein (LI) due to data constraints. These 1259 European NUTS3 counties/districts thus represent the base for generating linkages and nodes at the more aggregated NUTS1 level. Finally, we are especially interested in the *network centrality* and *connectedness* of the NUTS1 units. To understand

⁸ A complete concordance table of NUTS1, NUTS2, NUTS3 codes is offered by EUROSTAT (2009) and RegPAT (2009). Population threshold limits of NUTS levels are 150.000-800.000 (NUTS3), 800.000-3.000.000 (NUTS2) and 3.000.000-7.000.000 (NUTS1). The extracted patent data from OECD RegPAT (2009) are regionalized according to the NUTS2003 classification (Maraut et al., 2008; RegPat, 2008, 2009).

the complexity and dynamics of industries and their underlying inventorship-networks, we have to evaluate the position and centrality of actors, respectively regions, within the networks. The agents are in general inventors, who's postal addresses, which is their work place location, can be used to determine their location in geographical space and thus within large co-inventorship networks. We produce networks of counties/districts in which the intensity of interregional relationships (patenting collaborations) is reflected by the number of co-invented EPO patents. The NUTS3 level was explicitly chosen to unfold the existing spatial heterogeneity in terms of inventorship due to two observations: (i) *some counties do simply not innovate at all*, and (ii) *some regions, although they have EPO patent applications, are not connected to co-inventorship networks during the whole period; they are totally isolated*. Accordingly, these counties would bias measures at a higher spatial level by losing information on intra-NUTS1 co-patenting. Consequently, the counting of pure between-NUTS1 linkages would mean a severe loss of information, namely spatially localized co-inventorship linkages between NUTS3 units.⁹ Accordingly, the applied regionalization level of co-inventorship is very deep, focusing exclusively on small spatial units, where we assume much stronger effects from concentration, agglomeration and spatial proximity.

3.3 IPC - Technology Field Concordance

Aggregation and matching of the *International Patent Classification* (IPC) and the technology field classification is accomplished in this project by application of the *ISI-SPRU-OST-concordance* (Fraunhofer ISI, Karlsruhe, Germany, Observatoire des Sciences et des Techniques (OST), Paris, France and SPRU, University of Sussex, Brighton, UK) of Schmoch et al. (2003).¹⁰

This concordance uses the standard IPC and matches 838.792 EPO patent application IDs to 43 technology fields (TF)¹¹: TF1 Food, beverages (10.922 IDs); TF2 Tobacco products (597); TF3 Textiles (5.116); TF4 Wearing apparel (830); TF5 Leather articles (624); TF6 Wood products (808); TF7 Paper (6.222); TF9 Petroleum products, nuclear fuel (4.869); TF10 Basic chemical (84.506); TF11 Pesticides, agro-chemical products (9.168); TF12 Paints, varnishes (209); TF13 Pharmaceuticals (118.685); TF14 Soaps, detergents, toilet preparations

⁹ The empirical results have been illustrated in individual co-inventorship network graphs at the NUTS3 and NUTS1 level and are available upon request.

¹⁰ The IPC system (IPC revision 8.0) is an internationally agreed, non-overlapping hierarchical classification system that consists of eight sections (first level), 118 classes (second level), 628 subclasses (third level), 6.871 (fourth level) main groups and 57.324 subgroups (fifth level) to classify inventions claimed in the patent documents. The IPC divides patentable technology into eight key areas; A: Human Necessities; B: Performing Operations, Transporting; C: Chemistry, Metallurgy; D: Textiles, Paper; E: Fixed Constructions; F: Mechanical Engineering, Lighting, Heating, Weapons; G: Physics; H: Electricity. Within these areas technology is divided and subdivided to a detailed level, which allows the subject matter of a patent specification to be very thoroughly classified. Although there exist alternative concordance tables for aggregating and matching patent classes with industries (Evenson et al., 1991; Verspagen et al., 1994), the ISI-SPRU-OST concordance represents one of the most recent approaches to this issue (Schmoch et al., 2003).

¹¹ The overall number of linked EPO patent IDs is reported in brackets. According to Schmoch et al. (2003), TF8 Publishing & printing is not occupied.

(5.852); TF15 Other chemicals (9.487); TF16 Man-made fibres (1.652); TF17 Rubber and plastics products (23.941); TF18 Non-metallic mineral products (18.953); TF19 Basic metals (12.791); TF20 Fabricated metal products (16.451); TF21 Energy machinery (24.153); TF22 Non-specific purpose machinery (27.486); TF23 Agricultural and forestry machinery (5.639); TF24 Machine-tools (13.643); TF25 Special purpose machinery (38.973); TF26 Weapons and ammunition (1115); TF27 Domestic appliances (13.671); TF28 Office machinery and computers (57.929); TF29 Electric motors, generators, transformers (5.322); TF30 Electric distribution, control, wire, cable (8.040); TF31 Accumulators, battery (7.686); TF32 Lightning equipment (2.106); TF33 Other electrical equipment (7.928); TF34 Electronic components (30.951); TF35 Signal transmission, telecommunications (60.414); TF36 Television and radio receivers, audiovisual electronics (14.631); TF37 Medical equipment (55.248); TF38 Measuring instruments (46.526); TF39 Industrial process control equipment (7.339); TF40 Optical instruments (17.788); TF41 Watches, clocks (742); TF42 Motor vehicles (45.305); TF43 Other transport equipment (7.725); TF44 Furniture, consumer goods (6.749). The overall number of extracted patents with more than one inventor from different NUTS3 units for all OECD countries is 672.432. Due to the fact that technology fields consist of several IPC, the extracted and analyzed number of patent IDs for the OECD with respect to all 44 TF is 838.792.¹²

4 The Research Methodology

4.1 Social Network Analysis

In order to understand the complexity and dynamics of industries and their underlying co-inventorship-network structure, we have to evaluate the location and centrality of actors within EPO co-inventorship networks. In this respect, network importance of countries and regions is then reflected by the proxy variable *co-inventorship network centrality*. Conceptually, centrality indices normally measure how central an agent is positioned in a *scale-free network* or ego network. Scale-free networks are networks whose degree distributions follow a power law, at least asymptotically. As with all technological and economic systems characterized by such power law distributions, the most essential attribute of scale-free networks is the relative commonness of nodes with a degree that greatly exceeds the average. The highest-degree vertices are often called *network hubs*. Measuring the *network location* is finding the centrality of a node. The various possible centrality measures give us insights into the differing roles and

¹² We corrected the overall number of 838.792 patent IDs and cleaned all individual linkages that are not directed to one of the 1259 NUTS3 units within our European sample, e.g. Canada, USA, China, Japan, India. As a result, the overall number of unique IDs for our European sample is smaller compared to the OECD; the overall number of extracted linkages is 7.135.117. For comparison purpose of European co-inventorship, it is not meaningful building NACE sectors from IPC, although an IPC-NACE concordance table is available. Schmoch et al. (2003) simply link fractions of patents of one technology field to NACE industries. The paper is exclusively analyzing co-inventorship locations within patent documents in order to track co-inventorship linkages for different technology fields, which makes methods of fractional counting of patents by means of IPC-NACE concordance senseless (Maraut et al., 2008).

groupings within spatially organized networks. From a *core-periphery perspective*, it is then essential to depict the *hub-and-spoke structure* of technology fields. Within graph theory and network analysis, various centrality measures have been proposed to determine the relative importance of a node. To accomplish such an analysis and to get answers to our research questions, we make use of *degree centrality*, *betweenness centrality* and *eigenvector centrality*. The following subsection gives a brief summary of these measures.

4.2 Centrality Measures

Degree centrality is a very simple measure and is used as a standard measure of centrality. Network nodes which have more ties to other nodes may be in an advantaged positions. Because such nodes have many ties, they may have alternative ways to satisfy informational or commodity needs, and hence are less dependent on other individuals. Basically, the degree of a node in a network is then defined as the number of linkages or edges (but also nodes) which are connected with this node. Based on this measure the activity of a node in a network can be evaluated. Network research measures network activity for an agent by using the concept of degrees - the number of direct connections a node has. In order to know the standardized score, each score is divided by $n - 1$ (with $n =$ the number of nodes). In undirected data, actors differ from one another only in their number of connections. Degree centrality is defined and used in this paper for measuring the embeddedness of counties and regions, by taking the number of linkages (edges) of every spatial unit. The degree centrality of a county or region then represents its popularity within the network. Accordingly, degree centrality can be interpreted as the likelihood that the actors on a node get in contact with what is flowing through the network, by means of their linkages to their immediate vicinity. To normalize, degree centrality is divided by the number of other vertices/nodes theoretically reachable, which is the maximum number of all nodes within the network. If the network is directed (meaning that linkages or edges have a certain direction), then we usually define two separate measures of degree centrality, namely in-degree and out-degree centrality. In-degree is a measure of the number of linkages/edges directed to the vertex, and out-degree is the number of linkages/edges that the vertex directs to other vertices. We use undirected centrality measures as we have large scale-free networks.

Besides popularity of actors by means of the pure number of (unique) linkages, *betweenness centrality* (BC) is a complex measure that indicates to what extent vertices occur on the shortest paths between all other vertices. In social networks, the interaction of two agents, who are not connected might depend on a third agent who is on the path between the two. A problem might be, that the interaction is controlled by the third agent. Betweenness thus explores the bridge-function of some network members. Therefore, the mathematical algorithm calculates the position of the nodes/ vertices within the network. Betweenness centrality then illustrates to what degree information exchanged in the network will likely pass by a certain node or not due to its bridge-function. This centrality is then calculated as

the ratio of all geodesics between pairs of nodes which run through each node. The geodesic distance is the length of the shortest path between two connected nodes. The BC measure reflects how often an node lies on the geodesics between the other nodes of the network. Nodes with high betweenness have greater influence over what flows or not. Normalized betweenness centrality divides simple betweenness centrality by its maximum value. The measure of betweenness centrality ranges from 0 to 1. We use this index to say something about gatekeeping positions of regional units in EPO co-patenting.

Some linkages are more important than others. *Eigenvector centrality* not only considers the pure number of linkages, but also the importance of those connected neighbors, that mere degree centrality indices cannot provide. Eigenvector centrality is like a recursive version of degree centrality. The eigenvector approach is an effort to find the most central actors in terms of the global or overall structure of the network, and to pay less attention to patterns that are more local. The statistical method applied to do this is factor analysis. In a general way, what factor analysis does is to identify (latent) dimensions of the distances among nodes. The location of each node with respect to each dimension is called an eigenvalue, and the collection of such values is called the eigenvector. Therefore, eigenvector centrality is a measure of the importance of a vertex/node or agent in a network. It assigns relative scores to all vertices in the network based on the principle that connections to other high-scoring nodes (here counties and regions) contribute more to the score of the vertex under analysis than connections to low-scoring vertices. Eigenvector centrality scores correspond to the values of the first eigenvector of the graph adjacency matrix; these scores may, in turn, be interpreted as arising from a reciprocal process in which the centrality of each actor is proportional to the sum of the centralities of those actors to whom the region/county is connected. The normalized eigenvector centrality is the scaled eigenvector centrality divided by the maximum difference possible expressed as a percentage.

This project uses *degree centrality*, *betweenness centrality* and *eigenvector centrality* measures to analyze the hierarchical position of NUTS3 counties and NUTS1 regions by means of connectedness to other spatial units.

5 Empirical Results

5.1 Network Size, Regions, Within and Between Linkages

This section offers a short overview and provides general statistics for all 43 technology fields. A very first question we address is the following: *(i) Do technology fields differ in their overall network size?* In this respect, we have to calculate the *global descriptive statistics* of the networks: the overall number of nodes and co-patenting linkages, within and between NUTS3 counties and districts, but also linkages at the NUTS1 level. Additionally, we have to calculate the number of self-loops for each technology specific co-inventorship network in order to develop a general overview about network size and uniqueness of regional interaction.

First, we calculated additional global network metrics for all 43 technology fields, such as *overall number of nodes/vertices*, *graph density* and *average geodesic distance* as presented in figures 2, 3 and 4. The networks with the largest number of nodes are TF13 *pharmaceuticals* (159 nodes), TF10 *basic chemicals* (152), TF28 *office machinery and computers* (142), TF25 *special purpose machinery* (140), TF35 *signal transmission and telecommunication* (137). Additionally, these five networks also show high *network graph density* parameter values and low values of average geodesic distance.

< figures 2, 3 and 4 about here >

Second, we can derive from these graphs that co-patenting networks tremendously differ in their overall size in terms of linkages as presented in figures 5 and 6. We extracted the number of *overall within* and *between* NUTS1 linkages and *unique within* and *between* NUTS1 linkages. The largest co-patenting networks are TF13 *pharmaceuticals* (21,46% of all co-patenting linkages), TF10 *basic chemical* (9,52%), TF38 *measuring instruments* (6,38%), TF42 *motor vehicles* (6,34%), TF11 *pesticide and agrochemical products* (5,43%), TF37 *medical equipment* (4,60%), TF35 *signal transmission and telecommunication* (4,34%), TF28 *office machines and computer* (4,29%), TF25 *special purpose machinery* (4,29%), TF22 *non-special machinery* (3,60%). These ten technology fields already represent 5.011.141 linkages (70,23%) of all existing 7.135.117 linkages within the reference period. In opposition, the smallest ten networks are the following: TF5 *leather articles* (0,02%), TF12 *paints and varnishes* (0,03%), TF2 *tobacco products* (0,06%), TF26 *weapons and ammunition* (0,06%), TF16 *man made fibre* (0,06%), TF41 *watches and clocks* (0,06%), TF4 *wearing apparel* (0,06%), TF6 *wood products* (0,10%), TF32 *lighting equipment* (0,21%), TF9 *petroleum products and nuclear fuel* (0,30%). In total, the ten smallest networks only account for 0,95% of all linkages what validates the heterogeneity hypothesis.

< figures 5 and 6 about here >

Third, it seems to be a crucial information noting that only a few regions represent the majority of overall edges/linkages and that these co-patenting linkages are mainly intra-regional - within the same NUTS1 regions. This means that most co-patenting happens at a very *local scale* (between NUTS3). Figures 7 and 8 summarize these structural informations. We have calculated the share of *unique* within and between NUTS1 linkages but also the share of *overall* within and between NUTS1 linkages. Accordingly, most co-inventorship interaction in terms of EPO co-patenting happens within a few NUTS1 regions; e.g. Baden-Württemberg (DE1), Bavaria (DE2), Nordrhein-Westfalen (DEA), Rheinland-Pfalz (DEB), Ostschweiz (CH05), Ile-de-France (FR1), Centre-Est (FR7), Nord-Ovest (ITC), Madrid (ES3), London (UKI) and South-East (UKJ). Figure 9 shows the TOP5 linkages and compares the TOP5 ranking for *inter-* and *intra-regional* linkages. Bavaria (DE2), for example, represents 316.802 intra-regional linkages within TF13 *pharmaceuticals*; 118.769 intra-regional linkages in TF42 *motor*

vehicles; and 166.363 intra-regional linkages in TF38 *measuring instruments*. Baden-Württemberg (DE1) has a similar importance in TF42 *motor vehicles* with 105.451 intra-regional linkages and 23.654 intra-regional linkages in TF24 *machine tools*. Moreover, 60,15% of all EPO co-patenting linkages in the reference period are of intra-regional type; only 39,85% of all 7.135.117 linkages are between NUTS1 regions. Accordingly, our results confirm the hypothesis that the majority of co-patenting linkages is represented by only a few regions and that a large fraction of overall linkages is of intra-regional nature.

< figures 7 and 8 about here >

5.2 Centrality of Regions in Co-Inventorship Networks

In addition to the just presented descriptive statistics at the *macro level of the networks* (total network metrics), this subsection now centers the following research questions: *(ii) Which are the most connected regions in EPO co-patenting networks? (iii) Which regions represent the most essential industry leaders in a specific technology field? (iv) Which regions represent crucial within- and between-network bridges? (v) Which regions are the most isolated ones in European technology specific co-patenting networks?* In order to answer these questions, we calculate descriptive co-inventorship network statistics at the *micro level* (NUTS3, NUTS1).

Figure 9 and the tables 3, 4 and 5 provide the ranked order of NUTS1 regions that represent the most central regions within our EU27 sample of regions. Complete region labels are attached in figure 14 in the appendix. We distinguish between *eigenvector*, *degree* and *betweenness centrality*. It is absolutely visible from figure 9, that the TOP5 region pairs already represent large fractions of technology-specific co-patenting linkages. Moreover, these linkages are mainly intra-regional, meaning that they occur between NUTS3 counties within the same NUTS1 aggregate. Furthermore, we conclude that the most central regions are (in general) those that also show high values of overall EPO patenting (fractional counting). In this respect, we conclude that co-inventorship centrality within co-patenting networks is positively correlated with patent intensity. Tables 3, 4 and 5 finally highlight the TOP10 regions by means of co-patenting network centrality in ranked order for all technology fields.

< figure 9 and tables 3, 4 and 5 about here >

5.3 Co-Location of Technology-specific Co-inventorship Networks

Another serious research issue we approach is to what extent innovative regions have a similar (perhaps central) network position with respect to different technology fields (geographical coincidence). This analysis challenges the following crucial questions: *(vi) Are European regions characterized by a diversified technology base and multi-technology network hubs?* We assume that the most innovative regions obtain a central position in different technology fields by means of patent intensities. We explore the similarity of technology fields by

contrasting regions' ranking positions in all 43 technology fields. Therefore, we first calculate *Spearman rank correlation coefficients* for patent intensities by technology fields. A Spearman correlation coefficient $\rho = 1$ results when the two variables being compared are monotonically related, even if their relationship is not linear. In contrast, this does not give a perfect Pearson correlation.¹³ Our observations are patent intensities of the European NUTS3 units. If a region has a low value in terms of EPO patent applications (per million population) compared to other regions, a low ranking position is given to this unit.¹⁴ We calculate the correlations for the reference period 2000-2004. The degree of obtained Spearman correlations illustrate to what degree the respective patent intensity ranking of regions in two or more technology fields overlap. In other words: *To what degree do the respective technology fields center and co-locate in the same region?*¹⁵ We shaded Spearman coefficients between 0.5 and 0.7 in light grey, coefficients above 0.7 in dark grey. Additionally, it is worth noting that all correlation coefficients are significant at the 99%-level.¹⁶ With regard to the main hypothesis of this subsection, even a brief look at the first correlogram (patent intensity) illustrates that there exists indeed *clustering/co-location of several technological fields* in the same regions (with the same intensity). As a consequence, we conclude that *centers of innovation* seem to co-locate. Figure 10 represent the Spearman rank correlation coefficients for all 43 technology fields. We can identify several co-located technology fields (by patent intensity): TF10 *basic chemicals*, TF13 *pharmaceuticals*, TF15 *other chemicals*, TF37 *medical equipment* and TF38 *measuring instruments* share high correlation coefficients. High parameter values can be observed for TF42 *motor vehicles* and TF21 *energy machinery* what is an indication of co-location. Another co-location seems to exist between TF28 *office machinery and computers* and TF38 *measuring instruments*. We can also observe a high coefficient for TF35 *signal transmission and telecommunication* and TF28 *office machinery and computers*. Finally several machinery fields seem to co-locate in similar regions such as TF21 *energy machinery*, TF22 *non-special*

¹³ Calculating the correlation coefficient requires normally distributed data. In the case of non-normal distributions, Pearson's correlation coefficient will lead to wrong results. Spearman's rank correlation coefficient or Spearman's rho (ρ) is a non-parametric measure of statistical dependence between two variables. It assesses how well the relationship between two variables can be described using a monotonic function. If there are no repeated data values, a perfect Spearman correlation of +1 or -1 occurs when each of the variables is a perfect monotone function of the other. The Spearman correlation coefficient is often thought of as being the Pearson correlation coefficient between the ranked variables. In practice, however, a simpler procedure is to calculate ρ . The n raw scores X_i, Y_i are converted to ranks x_i, y_i , and the differences $d_i = x_i - y_i$ between the ranks of each observation on the two variables are calculated. In the case of tied observations (observations with identical parameter values), we have to take the arithmetic average of the rank numbers associated with the ties.

¹⁴ There are huge differences in the occupation of regions with patent applications by the 43 technology fields. More than one third of all 1259NUTS3 units do not innovate at all. The distribution shows non-normality in terms of skewness, kurtosis and percentile ratios.

¹⁵ We also computed Pearson's r and Kendall's tau correlation coefficients. However, due to the fact that the data are not normally distributed across regional units, we use Spearman rank correlation coefficients. Additionally, we are interested in the co-location pattern of patent intensity rankings.

¹⁶ A Bonferroni correction for alpha-failure cumulation shows that only five Spearman coefficients loose significance: (i) TF12 with TF4 and TF5; (ii) TF2 with TF29, TF30 and TF41.

purpose machinery, TF24 *machine tools* and TF25 *special purpose machinery*.¹⁷

< figure 10 about here >

Additionally, we test the hypothesis that the most innovative regions in terms of patent intensities also obtain a central position in different technology fields by means of *co-inventorship network centrality*. Therefore, we compare regions' ranking positions in technology-specific co-inventorship networks. We calculate Spearman rank correlation coefficients for co-inventorship centrality indices for all 43 technology fields. Observations are again the European NUTS3 units. We then take the extracted linkages between NUTS3 units and aggregate to the NUTS1 level for a treatment of inventor commuting between NUTS3 units and other labor market effects. If a region has a low network centrality in terms of co-inventorship compared to other regions, a low ranking position is given to this unit. If a region is not connected to the respective network at all, a centrality parameter value of zero is assigned to this unit. This happens for a certain number of regions. Finally, we use the rankings to calculate the correlation matrices for the reference period 2000-2004. The parameter value of obtained Spearman correlation coefficients illustrate to what degree the respective co-inventorship network centrality ranking of regions in two or more technology fields overlap. To illustrate our results, correlograms are again used to visualize the spatial pattern of co-location of technology-specific co-inventorship networks. We constructed such correlograms for all 43 networks, taking different centrality indices for calculation (degree centrality, eigenvector centrality, betweenness centrality). The network based correlograms visualize Spearman rank correlation coefficients of the centrality network ranking of regional units. The correlation coefficients are again shaded; coefficients between 0.5 and 0.7 in light grey, coefficients above 0.7 in dark grey. Additionally, all correlation coefficients are significant at the 99%-level.¹⁸ The correlograms thus present the similarity between co-inventorship networks by means of the different centrality ranking measures of the network nodes. High Spearman rank correlation coefficients between two technology fields then mean that two technology fields are similar in their network centrality patterns. Additionally, it is then a proxy for geographical coincidence of co-inventorship networks. Figures 11, 12 and 13 represent the Spearman rank correlation matrices by centrality index. However, it is worth remembering that the linkages are based on NUTS3 co-inventorship linkages. The aggregation to the NUTS1 level simply treats a linkage between NUTS3 units of the same NUTS1 region as a self loop and thus controls, again, for *inventor commuting* at the very disaggregated NUTS3 level. Therefore, the obtained results confirm the existence of multi-technology network hubs in Europe.

< figures 11, 12 and 13 about here >

¹⁷ Note that positive Spearman correlation coefficients (co-location) are not only a statistical artefact due to similar IPC fields.

¹⁸ Again, a Bonferroni correction for alpha-failure cumulation was performed without much difference.

First, we can observe that innovative regions, in general, have a central gatekeeping position (betweenness centrality) in several technology fields. TF10 *basic chemicals* and TF13 *pharmaceuticals* show a very high Spearman coefficient (0.83), which means that the central regions in the co-patenting network in TF10 *basic chemicals* also dominate the TF13 *pharmaceutical co-patenting network* and are essential for the overall connectedness of the whole network. Similarly, TF38 *measuring instruments* and TF13 *pharmaceuticals* co-locate in the same regions (0.84). Second, the correlogram for degree centrality (importance of regions in terms of overall number of unique linkages) shows again empirical evidence for the *multi-technology hub hypothesis*. Most networks co-locate in those regions that are central in several technology-specific co-patenting networks, which supports the diversification hypothesis. Third, the *eigenvector correlation matrix* highlights the correlation coefficients for all 43 technology fields in terms of important linkages (importance in terms of linkages to the most central regions). High Spearman coefficient values then mean that the technology-specific co-patenting networks are determined by the same regions and that those regions have many important linkages to other highly innovative regions and represent empirical evidence for dense networks. With regard to the hypotheses of this subsection, all four correlograms illustrate that there is indeed *co-location of technology fields in Europe*. When comparing degree centrality indices of European units, we can suggest that the most innovative counties (NUTS3) and regions (NUTS1) are indeed central for most technology-specific co-patenting networks (TF1 to TF44). It is absolutely clear from these tables that *centers of co-patenting* seem to co-locate in identical regions (NUTS1), which confirms the hypothesis that European regions are indeed *multi-field network nodes*. The Spearman rank correlation coefficients are much higher for eigenvector centrality indices than for betweenness or degree centrality, which makes us thinking about *dense networks among the most innovative regions*. Indeed, a comparison of regional IDs confirms this hypothesis.

6 Summary and Conclusion

This paper contributes with empirical findings to European *co-inventorship location* and *geographical coincidence of co-patenting networks* in several ways. Our analysis has to be recognized as a complementary approach to paper trail studies (patent citation analysis) and econometric estimations in the *knowledge production function* (KPF) tradition. We use extracted data from EPO patent applications from our own relational database that makes use of the OECD RegPAT (2009) files. Based on *co-patenting information* from EPO patent data for the reference period 2000-2004, we analyze 7.135.117 co-inventorship *linkages* in a spatial and technological context. European co-inventorship activity (co-patenting) is spatially linked to 1259 European NUTS3 units (EU25+CH+NO) by *inventor location*. The paper does consider co-inventorship networks of NUTS3 (counties) and NUTS1 units (regions) rather than networks of individuals, but maintaining that behind the spatial co-inventorship network lies

the network of individuals (inventors and their research collaborations). In this respect, we link different technology-specific co-inventorship networks to spatial units (counties, districts, regions). First, this paper puts forward an alternative approach for addressing the issue of *spatial dependence* and *spatial heterogeneity* in geographical innovation models, or, more general, in spatial innovation data. The significance of spatial autocorrelation of various variables and residuals in knowledge production function conceptualizations can be challenged, when taking into account the strong *connectedness* of counties, districts and regions and thus the presence of *research collaborations* within and between European spatial units in terms of co-patenting linkages. Second, we confirm the hypothesis that co-inventorship networks differ in their *overall size* (nodes, linkages, self-loops) as the ten largest technology networks represent 70,23% of all existing 7.135.117 linkages and the ten smallest networks only account for 0,95% of all linkages. Third, the paper offers statistical evidence for the presence of highly *localized European co-inventorship networks* for 43 technology fields, as the majority of co-patenting linkages between NUTS3 units (counties and districts) occur within the same NUTS1 regions (60,15% of all linkages). Although the networks are complex and heterogeneous (especially at the NUTS3 level), we identify a strong *local connectedness* between neighboring counties (NUTS3) and regions (NUTS1), which supports our argument that the majority of European co-inventorship collaborations are localized. Accordingly, our findings helps to understand the presence of positive spatial autocorrelation in regional innovation data. Fourth, the co-inventorship network analysis explicitly accounts for *different centrality measures* (betweenness, degree, eigenvector). In this respect, we present empirical evidence that European regions differ extremely in terms of network centrality. Thus, only a few European regions represent the most central co-patenting network nodes. Fifth, most co-patenting networks *co-locate* in those regions that are central in several technology-specific co-patenting networks, which supports the hypothesis of diversification of inventorship activity in Europe. We make use of our calculated network centrality indices for NUTS1 regions and calculate *Spearman rank correlation coefficients* for all 43 technology fields. It is then obvious from our correlation matrices that European centers of co-inventorship seem to *co-locate* in identical regions (NUTS1), which confirms the hypothesis that European regions are indeed *multi-field network nodes*. Finally, our correlation matrix for Spearman rank correlation coefficients of eigenvector centrality indices makes us thinking about *dense co-patenting networks* within and between the most innovative European regions.

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7 Appendix

Table 1: SQL Database Structure - EPO Patent Applications (RegPAT, 2008, 2009)

FILE 1: EP_APPLT_REG (EPO applicant)	FILE 2: EP_INVNT_REG (EPO inventorship)
2.126.580 hits	4.897.220 hits
Appln_id (PATSTAT application ident.)	Appln_id (PATSTAT application ident.)
Appln_nr (patent application nr.)	Appln_nr (patent application nr.)
Reg_code (NUTS3 region code)	Reg_code (NUTS3 region code)
Address	Address
Ctry_code (country code)	Ctry_code (country code)
Reg_share (share ≤ 1)	Reg_share (share ≤ 1)
Applt_share (applicant share ≤ 1)	Invnt_share (inventor share ≤ 1)
FILE 3: EP_PRIO_IPC (YEAR, IPC)	FILE 4: RegPAT_REGIONS (Concordance)
9.521.012 hits	Ctry_code (Country)
Appln_nr (patent application nr.)	Up_level_code (NUTS2 level code)
Appn_year (filing year)	Up_level_label (macro level region's name)
Prio_year (priority year of first filing)	Reg_code (NUTS3 level code)
IPC (IPC classes 8th edition)	Reg_label (micro level region's name)
FILE 5: IPC Concordance	
628 IPC fields vs. 44 technology fields	
628 IPC fields vs. 44 NACE fields	

Source: Own illustration. Notes: The OECD RegPAT (2008, 2009) dataset includes regionalized spatial units according to OECD Territorial Levels TL2 (macro region) and TL3 (micro region). For Belgium, Greece and the Netherlands, the OECD TL3 corresponds to the EUROSTAT NUTS2 level. All existing NUTS3 levels are regionalized via inventor address (ZIP code and/or city name).

Table 2: RegPAT data and the NUTS classification

Country Code	Country Name	Micro-Regions (NUTS3)	Meso-Regions (NUTS2)	Macro-Regions (NUTS1)	Inventor addresses
AT	Austria	35 NUTS3	9 NUTS2	3 NUTS1	43.084
BE	Belgium	43 NUTS3	11 NUTS2	3 NUTS1	48.362
CH	Switzerland	26 NUTS3	7 NUTS2	7 NUTS1	105.939
CY	Cyprus	1 NUTS3	1 NUTS2	1 NUTS1	168
CZ	Czech Republic	14 NUTS3	8 NUTS2	8 NUTS1	2.956
DE	Germany	439 NUTS3	41 NUTS2	16 NUTS1	940.797
DK	Denmark	15 NUTS3	1 NUTS2	1 NUTS1	32.851
EE	Estonia	5 NUTS3	1 NUTS2	1 NUTS1	323
ES	Spain	52 NUTS3	19 NUTS2	7 NUTS1	25.689
FI	Finland	20 NUTS3	5 NUTS2	4 NUTS1	47.212
FR	France	100 NUTS3	26 NUTS2	9 NUTS1	302.475
GR	Greece	51 NUTS3	13 NUTS2	4 NUTS1	2061
HU	Hungary	20 NUTS3	7 NUTS2	3 NUTS1	12.719
IE	Ireland	8 NUTS3	2 NUTS2	2 NUTS1	8.021
IT	Italy	103 NUTS3	21 NUTS2	5 NUTS1	125.173
LT	Lithuania	10 NUTS3	1 NUTS2	10 NUTS1	309
LU	Luxembourg	1 NUTS3	1 NUTS2	1 NUTS1	2.923
LV	Latvia	6 NUTS3	1 NUTS2	6 NUTS1	360
MT	Malta	2 NUTS3	1 NUTS2	2 NUTS1	106
NL	Netherlands	40 NUTS3	12 NUTS2	4 NUTS1	95.286
NO	Norway	19 NUTS3	7 NUTS2	7 NUTS1	15.691
PL	Poland	45 NUTS3	16 NUTS2	6 NUTS1	3.809
PT	Portugal	30 NUTS3	7 NUTS2	3 NUTS1	1.433
SE	Sweden	21 NUTS3	8 NUTS2	8 NUTS1	86.369
SI	Slovenia	12 NUTS3	1 NUTS2	12 NUTS1	1.939
SK	Slovak Republic	8 NUTS3	4 NUTS2	4 NUTS1	731
UK	United Kingdom	133 NUTS3	37 NUTS2	12 NUTS1	237.390
Σ	27 NUTS0	1259 NUTS3	268 NUTS2	149 NUTS1	2.144.176

Source: own illustration. Notes: The relational database includes regionalized spatial units according to OECD Territorial Levels TL2 (macro region) and TL3 (micro region) that . For Belgium, Greece and the Netherlands, the OECD TL3 corresponds to the EUROSTAT NUTS2 level. All existing NUTS3 levels are regionalized via inventor address (ZIP code and/or city name). The NUTS1 level explicitly considers extra-territory values for each member state.

Figure 1: Data selection method for inter-regional co-inventorship network analysis based on EPO patent applications 2000-2004

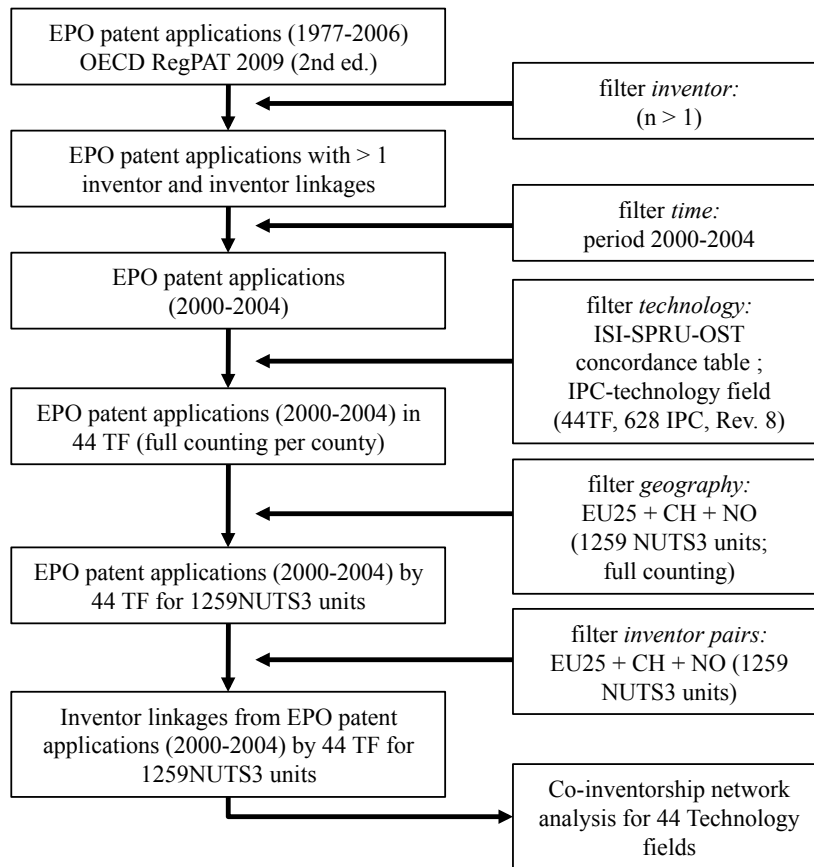
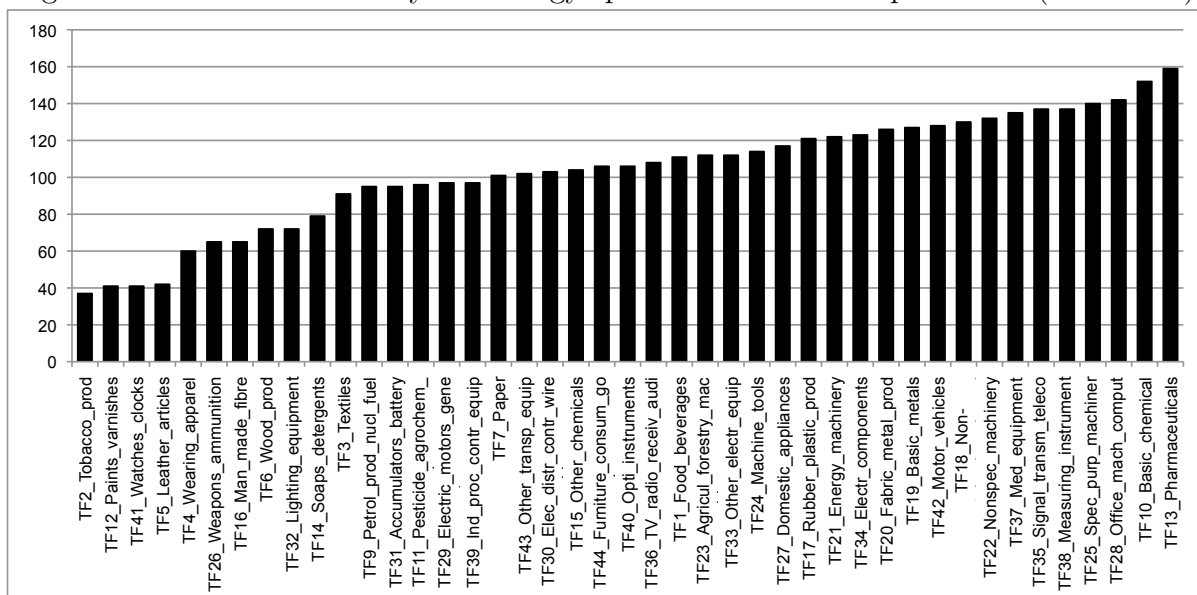
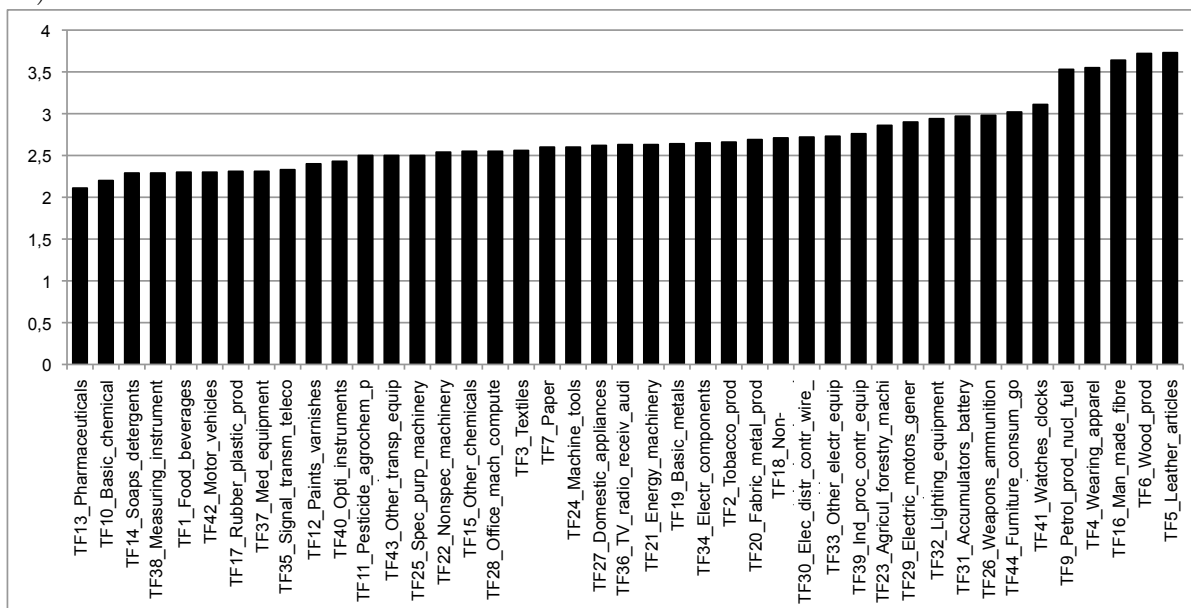


Figure 2: Number of nodes by technology-specific co-inventorship network (2000-2004)



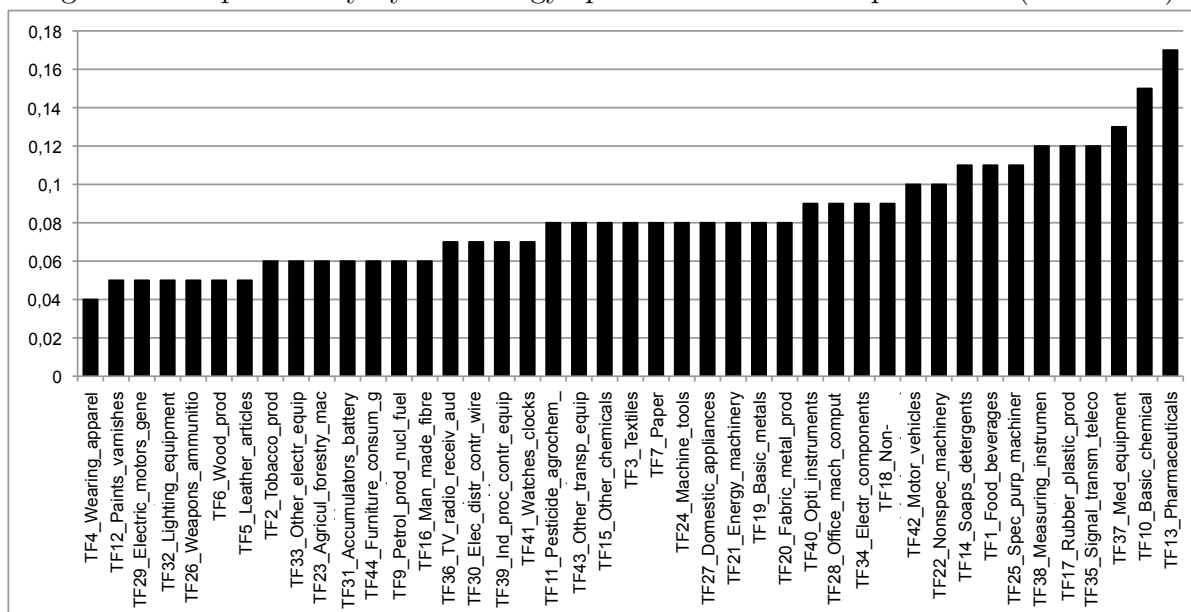
Source: own calculations and illustration; Notes: network nodes (regions) and edges (linkages) calculated by MySQL database extractions from OECD RegPAT (2008, 2009).

Figure 3: Average geodesic distance by technology-specific co-inventorship network (2000-2004)



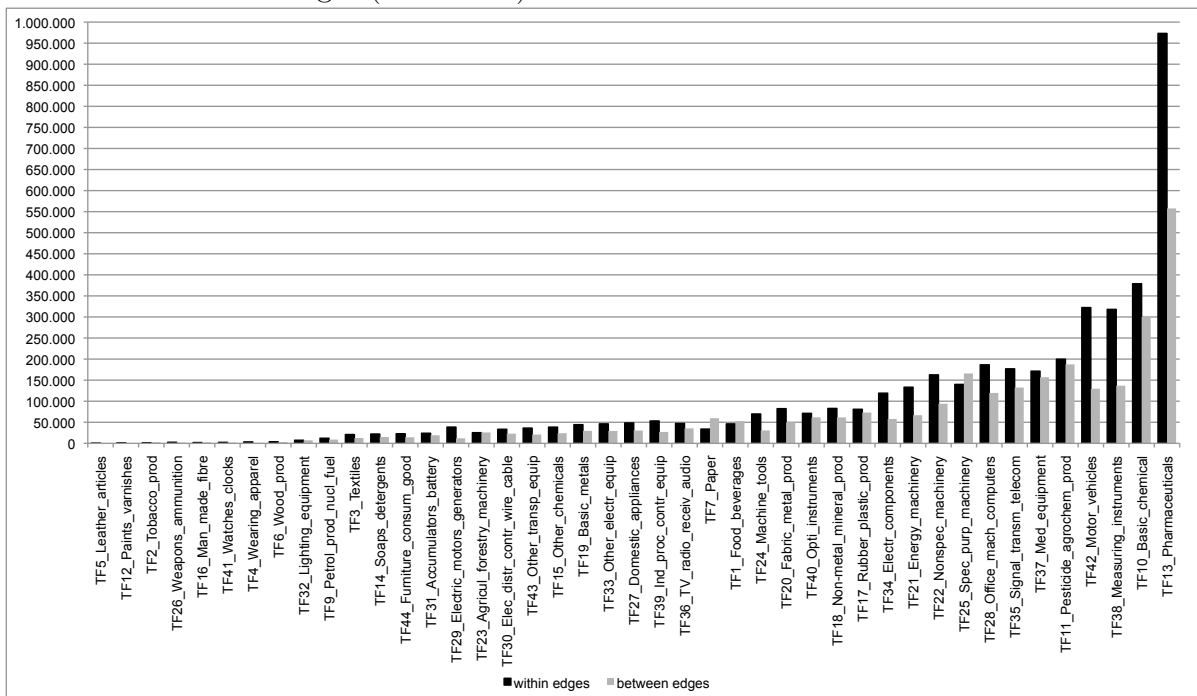
Source: own calculations and illustration; Notes: network nodes (regions) and edges (linkages) calculated by MySQL database extractions from OECD RegPAT (2008, 2009).

Figure 4: Graph density by technology-specific co-inventorship network (2000-2004)



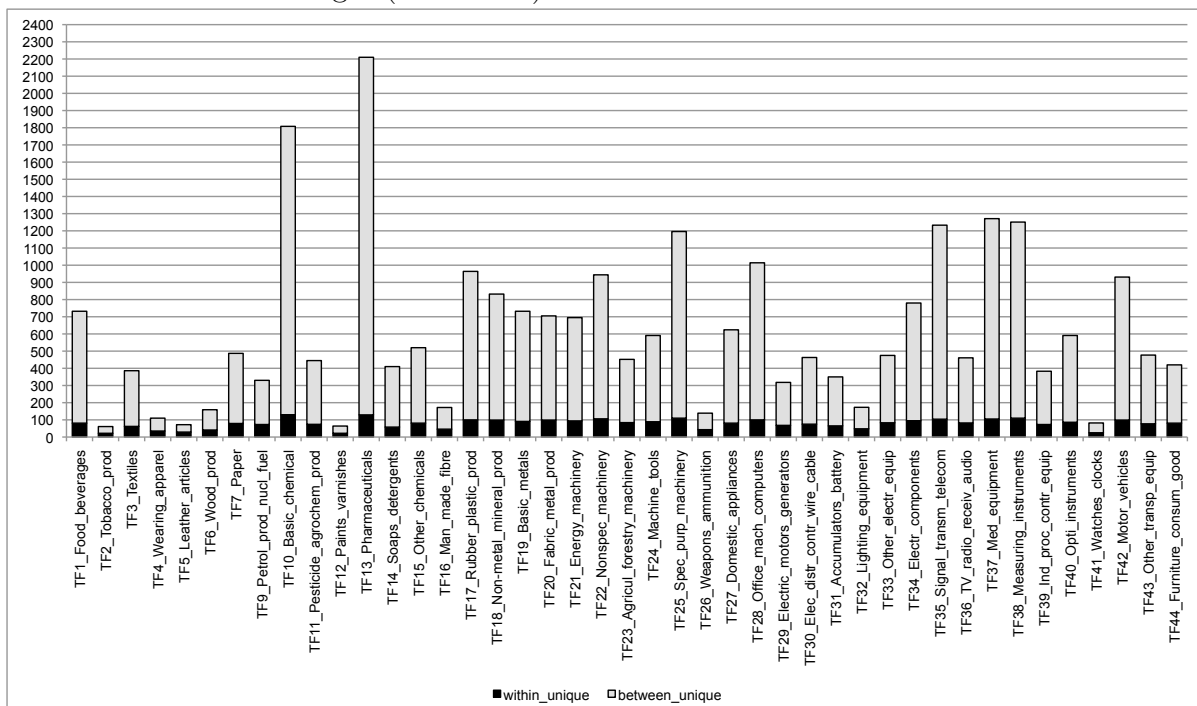
Source: own calculations and illustration; Notes: network nodes (regions) and edges (linkages) calculated by MySQL database extractions from OECD RegPAT (2008, 2009).

Figure 5: Structure of European co-patenting by technology field: number of overall NUTS1 within and between linkages (2000-2004)



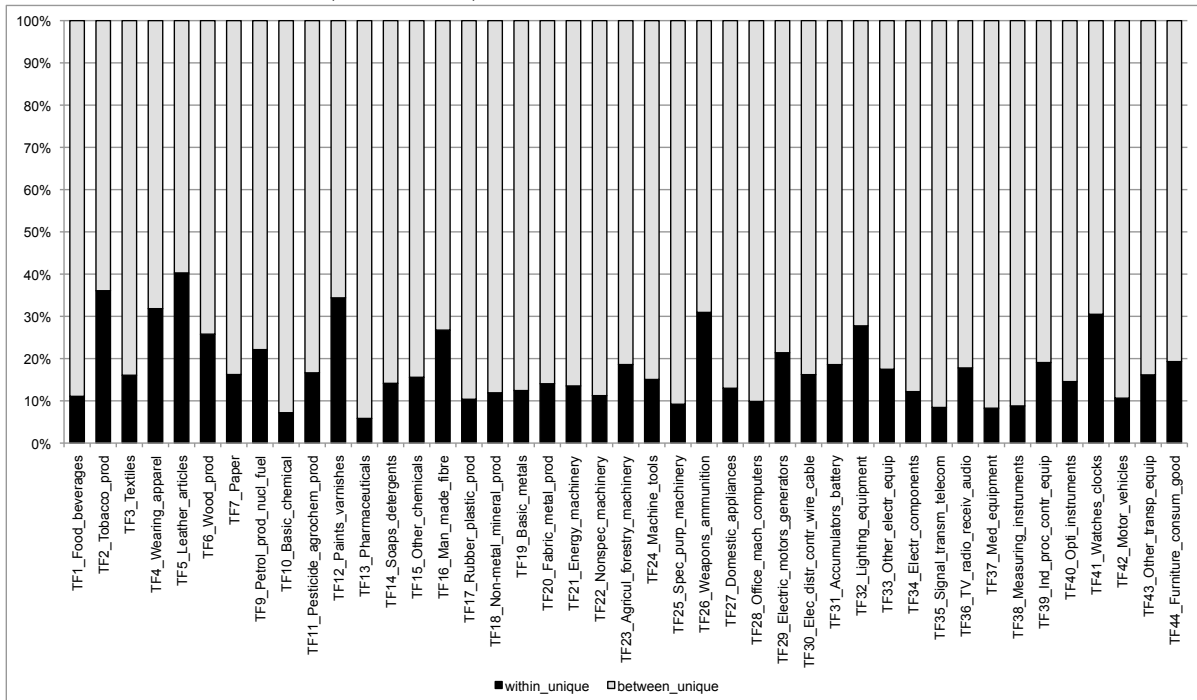
Source: own calculations and illustration; Notes: network nodes (regions) and edges (linkages) calculated by MySQL database extractions from OECD RegPAT (2008, 2009).

Figure 6: Structure of European co-patenting by technology field: number of unique within and between NUTS1 linkages (2000-2004)



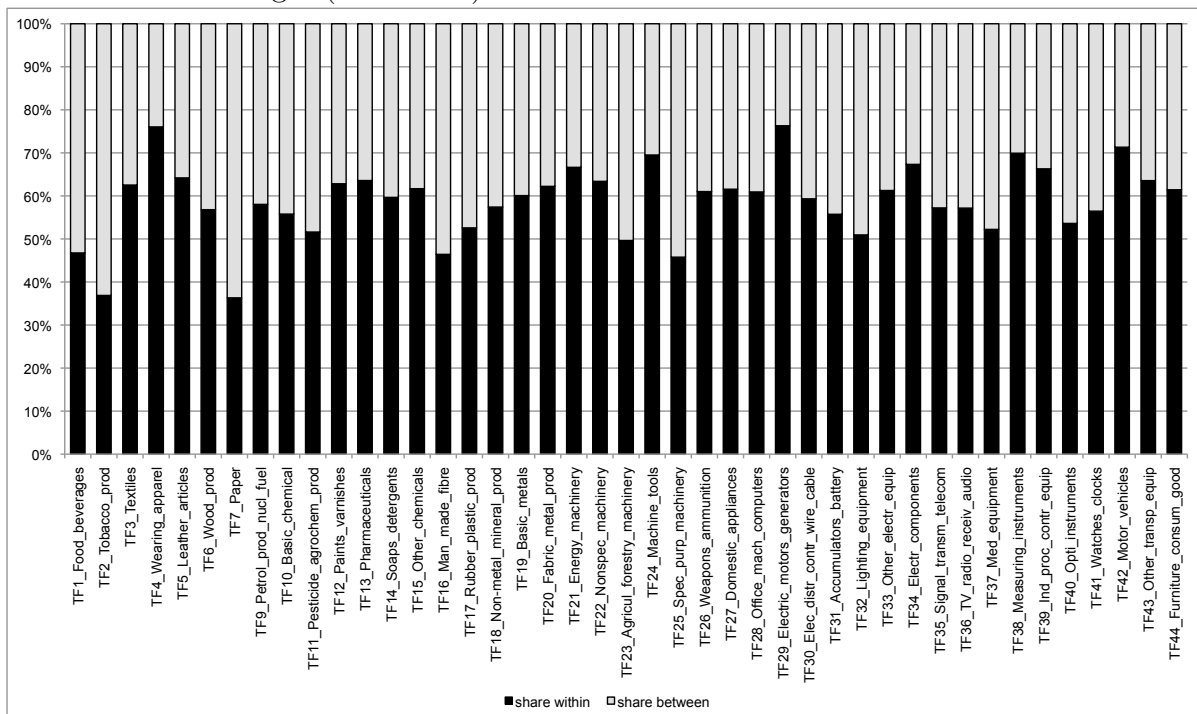
Source: own calculations and illustration; Notes: network nodes (regions) and edges (linkages) calculated by MySQL database extractions from OECD RegPAT (2008, 2009).

Figure 7: Structure of European co-patenting by technology field: share of unique within and between NUTS1 linkages (2000-2004)



Source: own calculations and illustration; Notes: network nodes (regions) and edges (linkages) calculated by MySQL database extractions from OECD RegPAT (2008, 2009).

Figure 8: Structure of European co-patenting by technology field: share of overall within and between NUTS1 linkages (2000-2004)



Source: own calculations and illustration; Notes: network nodes (regions) and edges (linkages) calculated by MySQL database extractions from OECD RegPAT (2008, 2009).

Table 3: Ranking Top 10 Regions by Degree Centrality for 44 Technology Fields

TF	1	2	3	4	5	6	7	8	9	10
TF1	NL3	DEA	DE1	DE2	CH01	BE2	CH02	DK0	DE9	FR1
TF2	UKJ	DE6	DEA	DEF	NL3	DE2	DE9	SE04	DE3	CH02
TF3	DE1	DE7	DEA	DE2	CH05	UKJ	UKD	BE2	UKE	FR4
TF4	FR7	DE7	DE1	ITF	ITD	DEA	ITC	FR2	DE2	ES5
TF5	DE1	DEA	ITD	DE2	DE9	DEB	UKI	ITE	UKF	CH04
TF6	DE9	DEA	DE1	DE2	CH04	CH05	CH03	DED	AT3	DE8
TF7	DE1	DE2	DEA	DE7	DEB	SE0A	DED	DE9	DEE	FR4
TF9	DEA	FR1	UKJ	UKD	NL3	FR2	DEB	FR7	ITC	FR8
TF10	DE1	DEA	DE7	DE2	BE2	FR1	UKJ	NL3	CH05	DEB
TF11	DEA	DE1	UKJ	DE7	DEB	DE2	FR7	FR1	CH05	BE2
TF12	DEA	CH01	DEB	DE2	DE1	CH05	DEF	DE7	FR2	CH04
TF13	DE1	DEA	FR1	DE2	UKJ	DE7	NL3	CH05	BE2	DK0
TF14	DEA	DE1	BE2	NL3	UKD	FR1	BE1	DEB	UKE	DE7
TF15	DEA	DE1	DE2	BE2	DE7	FR7	NL3	DEB	FR1	UKJ
TF16	DE1	DEA	DE7	DEB	BE2	FR4	DEE	DE2	FR7	FR1
TF17	DEA	DE1	DE2	DE7	DE9	BE2	DEB	CH02	CH01	FR1
TF18	DEA	DE2	DE7	FR1	DE1	DE9	CH05	ITC	FR2	DEB
TF19	DEA	DE2	DE7	DE1	CH05	DE9	AT3	FR1	FR7	CH01
TF20	DE1	DEA	DE2	DE7	DE9	BE2	FR1	UKJ	DEB	UKG
TF21	DE1	DE2	DEA	DEB	DE7	CH05	ITC	FR1	DEC	FR4
TF22	DE1	DEA	DE2	DEB	DE7	BE2	CH05	UKJ	ITD	ITC
TF23	DE1	DEA	FR1	DE2	DEB	DE9	FR4	NL2	DE7	BE2
TF24	DE1	DEA	DE2	DE9	CH05	DE7	UKH	FR4	ITC	CH04
TF25	DE1	DEA	DE2	DE7	UKJ	DE9	FR4	NL3	FR1	CH02
TF26	DE2	DEA	DE9	DE1	DEF	FR1	CH05	CH04	DEG	DE7
TF27	DE2	DE1	DEA	FR1	CH05	DE7	UKJ	BE2	DEB	UKI
TF28	DE1	DE2	UKJ	DEA	UKI	FR1	DE7	CH05	UKH	FR7
TF29	DE1	DE2	FR4	DEA	CH05	DE9	FR1	DE7	CH04	CH06
TF30	DE1	DEA	DE7	DE2	ITC	CH05	FR1	DEB	FR7	CH03
TF31	DE1	DEA	DE7	DE2	UKJ	DE9	CH05	DEF	CH02	CH01
TF32	DE2	DE1	DEA	DE7	UKJ	AT3	CH03	DE9	CH05	CH02
TF33	DE1	DE2	DEA	DE9	CH05	CH04	SE02	FR1	DE7	FR7
TF34	DE2	DE1	FR1	DEA	UKH	DE7	DEB	BE2	CH02	CH05
TF35	DE2	DE1	DEA	UKJ	SE01	ITC	UKH	UKK	FR1	CH02
TF36	DE2	DE1	DEA	FR1	UKJ	UKI	DE9	NL3	CH05	FR7
TF37	DE1	DE2	DEA	DE7	FR1	UKJ	CH04	CH02	CH05	CH01
TF38	DE1	DE2	DEA	DE7	FR1	UKJ	UKI	CH05	DE3	CH02
TF39	DE1	DE2	DEA	DEB	CH05	FR1	DE9	FR4	DE7	UKJ
TF40	DE2	DE1	DEA	DE7	CH05	FR1	UKJ	BE2	DE9	DEG
TF41	CH02	CH01	CH03	DE1	FR4	DEA	CH04	DE2	DE7	CH05
TF42	DE1	DEA	DE2	DE7	DEB	FR1	DE9	FR2	ITC	UKG
TF43	DE2	DE1	DEA	DE9	DE7	CH05	CH04	NL3	UKF	FR1
TF44	DE1	UKI	DE2	DEA	DE9	CH02	ITC	UKJ	UKH	CH03

Source: own illustration and calculation; Notes: based on own mySQL database.

Table 4: Ranking Top 10 Regions by Eigenvector Centrality for 44 Technology Fields

TF	1	2	3	4	5	6	7	8	9	10
TF1	DEA	DE1	NL3	CH01	CH02	DE2	DE9	DE7	FR1	CH05
TF2	DE6	DEF	DEA	DE9	DE3	DE2	DE8	UKJ	DEB	SE04
TF3	DE1	DEA	DE7	DE2	CH05	DEB	FR4	ES5	BE2	ITC
TF4	DE7	DE1	ITF	ITD	ITC	ITE	ES5	FR7	DE2	DEB
TF5	DEA	DE1	DE2	DE9	DEB	UKI	UKF	NL3	DE7	DEC
TF6	DE9	DE2	DEA	CH04	DE1	CH05	CH03	DE7	DEB	DED
TF7	DE1	DE2	DE7	DEA	DEB	DE9	CH02	CH05	FR4	CH01
TF9	DEA	FR2	FR1	NL3	UKD	FR8	BE2	UKJ	FR7	DEB
TF10	DE1	DE7	DEA	DE2	BE2	FR1	CH05	NL3	DEB	UKJ
TF11	DEA	DE1	DE2	DEB	DE7	FR7	UKJ	FR1	BE2	CH05
TF12	SI00D	SI00E	SI009	SI00B	SI00A	DEA	DEB	DE2	DE1	CH01
TF13	DE1	DE2	FR1	DEA	NL3	UKJ	CH05	DE7	BE2	CH01
TF14	DEA	DE1	BE2	BE1	UKE	DEB	UKD	DE7	UKJ	UKC
TF15	DEA	DE2	DE1	FR7	DE9	BE2	DEB	DE7	CH05	CH02
TF16	DE1	DE7	DEB	DEA	DED	DE2	DEE	BE2	DEG	DEZ
TF17	DEA	DE2	DE9	PL1	NL3	CH02	NO01	DE7	DE1	CZ06
TF18	AT2	DE7	DEA	SI00E	FR1	DE2	SE04	FR2	CH05	DE1
TF19	DEA	DE2	DE7	DE1	CH05	DE9	AT3	FR7	FR1	CH04
TF20	DE1	DEA	DE2	DE7	DE9	DEB	FR4	AT3	UKJ	FR1
TF21	DE1	DE2	DEA	DEB	DE7	UKF	DE3	CH05	UKH	FR1
TF22	DE1	DEA	DE2	DEB	DE7	CH05	BE2	ITD	UKJ	UKH
TF23	DE1	DEB	DEA	FR1	DE2	DE9	FR4	DE7	NL2	NL4
TF24	DE1	DEA	DE2	DE9	CH05	DE7	CH04	AT3	CH02	DED
TF25	DE1	DEA	DE2	DE7	DE9	UKJ	FR1	CH02	FR4	NL3
TF26	DEA	DE9	DE2	DEF	DE1	DE7	DEG	DEB	DE6	CH05
TF27	DE2	DE1	DEA	CH05	FR1	DE7	UKD	UKI	UKJ	DEB
TF28	DE1	DE2	UKJ	DEA	UKI	CH05	DE7	FR1	UKH	FR7
TF29	DE1	DE2	CH05	FR4	DEA	CH06	CH04	CH01	CH02	CH03
TF30	DE1	DEA	DE7	DE2	CH05	ITC	CH03	CH02	FR1	DEB
TF31	DE1	DE7	DEA	DE2	DE9	DE4	DEF	DED	DEB	CH05
TF32	DE2	DE1	DEA	DE7	AT3	UKJ	DE9	CH03	DEB	DEF
TF33	DE1	DE2	DEA	DE9	CH05	CH04	DE3	DEB	DE7	FR7
TF34	DE2	DE1	FR1	DEA	UKH	DEB	DE7	CH05	CH02	BE2
TF35	DE2	DE1	DEA	UKJ	ITC	UKK	SE01	UKH	FR1	BE2
TF36	DE1	DE2	DEA	DE9	NL3	FR1	CH05	CH01	UKI	FR7
TF37	DE1	DE7	DE2	DEA	FR1	CH04	CH02	UKJ	CH05	CH01
TF38	DE2	DE1	DE7	DEA	FR1	CH05	DE3	CH02	UKJ	DEB
TF39	DE1	DE2	DEA	DEB	DE7	CH05	DE9	DE4	DEG	DED
TF40	DE2	DE1	DE7	DEA	CH05	FR1	BE2	DE9	CH02	DEG
TF41	CH02	CH01	CH03	CH04	FR4	CH05	CH06	FR7	UKI	DE1
TF42	DE1	DE2	DEA	DEB	DE7	DE9	FR1	FR2	ITC	FR4
TF43	DE2	DE1	DEA	DE7	DE9	DE6	CH04	CH05	DE3	DEF
TF44	DE1	UKI	DEA	DE2	ITC	CH02	DE9	CH01	UKH	CH03

Source: own illustration and calculation; Notes: based on own mySQL database.

Table 5: Ranking Top 10 Regions by Betweenness Centrality for 44 Technology Fields

TF	1	2	3	4	5	6	7	8	9	10
TF1	NL3	DEA	DK0	BE2	DE2	DE1	SE04	ITD	UKH	CH02
TF2	DEA	UKJ	DE6	DEF	SE04	UKD	UKI	DEB	DE2	FR1
TF3	DE7	DE1	BE2	DEA	DE2	UKD	UKE	ITC	FR1	FR2
TF4	FR7	DE1	DE7	ES5	UKF	UKD	CH03	ITD	DEA	CH05
TF5	DE1	DEA	DE2	ITD	UKI	NL3	DEB	DE9	UKF	DEG
TF6	DE9	CH03	DEA	FR1	NL4	NL3	DED	FR2	FR4	NL2
TF7	DE1	DEA	DED	DE7	DE2	DEE	UKJ	SE0A	DE9	UKD
TF9	NL2	SE06	NL3	UKH	UKD	DEA	ITD	DE1	SE08	NO01
TF10	DEA	DE1	ES5	DE7	FR1	DE2	FR7	AT1	DED	ITD
TF11	DEA	UKJ	SE04	DE7	DE1	CH05	FR7	BE2	ES5	UKH
TF12	DE2	DEA	CH01	CH05	DEB	DE4	DEF	DE1	FR2	FR6
TF13	DE1	DEA	DK0	FR1	DE7	SE01	AT1	ES5	DE2	UKJ
TF14	DEA	BE2	DE1	FR1	NL3	DE7	UKD	UKE	DK0	BE1
TF15	DEA	DE1	ITC	NL3	SE04	BE2	DE2	DE7	UKJ	FR1
TF16	DE1	ITC	FR4	ITD	UKG	BE2	DE7	CH04	UKK	DEB
TF17	DEA	DE2	DE9	PL1	NL3	CH02	NO01	DE7	DE1	CZ06
TF18	AT2	DE7	DEA	SI00E	FR1	DE2	SE04	FR2	CH05	DE1
TF19	DEA	DE2	AT2	AT1	DE7	SE02	AT3	FR2	CH05	SI00E
TF20	DEA	DE1	DE2	UKG	BE3	BE2	SE0A	SI004	LU0	FR1
TF21	DE1	DEA	DE2	NL3	DEC	ITC	SE0A	SI004	DE9	CH05
TF22	AT1	DE1	DE2	DEA	DEB	BE2	SI004	NO03	SE01	ITC
TF23	FR1	DE2	DE1	DEA	SE01	DE9	DEB	NL4	FR6	BE2
TF24	DE1	DEA	DE2	FR2	DE7	CH05	SE0A	CH04	CZ01	SE02
TF25	DE7	SI00D	DE1	DEA	DE2	UKJ	CH02	DE6	FR1	CH05
TF26	DE2	FR1	CH04	DE1	DEA	DE9	CH05	DE6	FR8	DED
TF27	DE2	DE1	DEA	DK0	FR1	DE7	BE2	SE02	SE01	UKJ
TF28	DK0	UKJ	DE1	DEA	DE2	SI00E	FR1	CH02	NO01	ES5
TF29	DE1	DE2	SE02	CH05	ITC	NL4	DEA	FR4	FR1	CH06
TF30	DE7	DEA	ITC	CH05	FR1	DE2	DE1	BE2	SI00E	SE02
TF31	DE1	UKJ	DEA	DE2	DK0	DE7	SE06	DE9	ITE	ES3
TF32	DE2	DE1	UKJ	FR1	DEA	CH03	UKK	DE7	AT3	DE9
TF33	DEA	DE2	DE1	SE02	DE9	FR6	UKJ	CH05	BE3	FR1
TF34	DE2	DE1	AT2	SI00E	IE02	FR1	DEA	BE2	DE7	UKH
TF35	DE2	DE1	UKJ	SE01	SI00E	CH02	DEA	SI002	FR1	NO01
TF36	DE2	UKJ	DE1	UKI	FR1	DK0	DEA	NL3	FR7	DE9
TF37	DE1	DEC	CH01	FR1	DEA	ITD	DK0	SI00E	UKJ	DE2
TF38	DE1	DE2	SE01	DEA	FR1	ITD	DE7	NL3	UKJ	SE02
TF39	DE1	DE2	DEA	UKJ	CH05	ITC	DEB	SE0A	SE04	FR1
TF40	SE01	DE2	DE1	DE7	DEA	UKJ	CH05	FR1	FR7	BE2
TF41	DE1	DE2	CH01	DEA	CH02	FR4	NL4	CH04	CH05	CH03
TF42	DE1	DEA	DE2	DE7	FR1	SE0A	DE9	ITC	UKH	FR2
TF43	DE2	DE9	ITC	DE1	DEA	NL3	CH05	UKH	DE7	UKF
TF44	DK0	UKI	DE1	SI00E	DE2	DE9	NL4	NO03	DEA	SE0A

Source: own illustration and calculation; Notes: based on own mySQL database.

Figure 14: NUTS 2003 Classification

Code	NUTS	Code	NUTS	Code	NUTS	Code	NUTS				
1	AT	OSTERREICH	52	ES5	ESTE	103	LT007	Taurages apskritis	154	SI002	Podravska
2	AT1	OSTÖSTERREICH	53	ES6	SUR	104	LT008	Telsiu apskritis	155	SI003	Koroska
3	AT2	SÜDÖSTERREICH	54	ES7	CANARIAS	105	LT009	Utenos apskritis	156	SI004	Savinjska
4	AT3	WESTÖSTERREICH	55	ESZ	EXTRA-REGIO	106	LT00A	Vilniaus apskritis	157	SI005	Zasavska
5	ATZ	EXTRA-REGIO	56	FI	SUOMI / FINLAND	107	LTZ	EXTRA-REGIO	158	SI006	Spodnjeposavska
6	BE	BELGIQUE-BELGIË	57	FI13	Itä-Suomi	108	LU	LUXEMBOURG (GRAND-DUCHÉ)	159	SI009	Gorenjska
7	BE1	RÉGION DE BRUXELLES-CAPITALE	58	FI18	Etelä-Suomi	109	LU0	LUXEMBOURG (GRAND-DUCHÉ)	160	SI00A	Notranjsko-kraska
8	BE2	VLAAMS GEWEST	59	FI19	Länsi-Suomi	110	LUZ	EXTRA-REGIO	161	SI00B	Goriska
9	BE3	REGION WALLONNE	60	FI1A	Pohjois-Suomi	111	LV	LATVIJA	162	SI00C	Obalno-kraska
10	BEZ	EXTRA-REGIO	61	FI20	Åland	112	LV003	Kurzeme	163	SI00D	Jugovzhodna Slovenija
11	CY	KYPROS / KIBRIS	62	FIZ	EXTRA-REGIO	113	LV005	Latgale	164	SI00E	Osrednjeslovenska
12	CY0	KYPROS / KIBRIS	63	FR	FRANCE	114	LV006	Rīga	165	SIZ	EXTRA-REGIO
13	CZ	CESKA REPUBLIKA	64	FR1	ÎLE DE FRANCE	115	LV007	Pierīga	166	SK	SLOVENSKA REPUBLIKA
14	CZ01	Praha	65	FR2	BASSIN PARISIEN	116	LV008	Vidzeme	167	SK01	Bratislavsky kraj
15	CZ02	Strední Čechy	66	FR3	NORD - PAS-DE-CALAIS	117	LV009	Zemgale	168	SK02	Zapadne Slovensko
16	CZ03	Jihozapad	67	FR4	EST	118	LVZ	EXTRA-REGIO	169	SK03	Stredne Slovensko
17	CZ04	Severozapad	68	FR5	OUEST	119	MT	MALTA	170	SK04	Vychodne Slovensko
18	CZ05	Severovýchod	69	FR6	SUD-OUEST	120	MT001	Malta	171	SKZ	EXTRA-REGIO
19	CZ06	Jihovýchod	70	FR7	CENTRE-EST	121	MT002	Gozo and Comino/Ghawdex u Kemmuna	172	UK	UNITED KINGDOM
20	CZ07	Strední Morava	71	FR8	MEDITERRANÉE	122	MTZ	EXTRA-REGIO	173	UKC	NORTH EAST
21	CZ08	Moravskoslezsko	72	FR9	DÉPARTEMENTS D'OUTRE-MER	123	NL	NEDERLAND	174	UKD	NORTH WEST
22	CZZ	EXTRA-REGIO	73	FRZ	EXTRA-REGIO	124	NL1	NOORD-NEDERLAND	175	UKE	YORKSHIRE AND THE HUMBER
23	DE	DEUTSCHLAND	74	GR	ELLADA	125	NL2	OOST-NEDERLAND	176	UKF	EAST MIDLANDS
24	DE1	BADEN-WÜRTTEMBERG	75	GR1	VOREIA ELLADA	126	NL3	WEST-NEDERLAND	177	UKG	WEST MIDLANDS
25	DE2	BAYERN	76	GR2	KENTRIKI ELLADA	127	NL4	ZUID-NEDERLAND	178	UKH	EAST OF ENGLAND
26	DE3	BERLIN	77	GR3	ATTIKI	128	NLZ	EXTRA-REGIO	179	UKI	LONDON
27	DE4	BRANDENBURG	78	GR4	NISIA AIGAIUO, KRITI	129	PL	POLSKA	180	UKJ	SOUTH EAST
28	DE5	BREMEN	79	GRZ	EXTRA-REGIO	130	PL1	CENTRALNY	181	UKK	SOUTH WEST
29	DE6	HAMBURG	80	HU	MAGYARORSZAG	131	PL2	POLUDNIOWY	182	UKL	WALES
30	DE7	HESEN	81	HU1	KÖZEP-MAGYARORSZAG	132	PL3	WSCHODNI	183	UKM	SCOTLAND
31	DE8	MECKLENBURG-VORPOMMERN	82	HU2	DUNANTUL	133	PL4	POLNOCNO-ZACHODNI	184	UKN	NORTHERN IRELAND
32	DE9	NIEDERSACHSEN	83	HU3	ALFOLD ES ESZAK	134	PL5	POLUDNIOWO-ZACHODNI	185	UKZ	EXTRA-REGIO
33	DEA	NORDRHEIN-WESTFALEN	84	HUZ	EXTRA-REGIO	135	PL6	POLNOGNY	186	CH	SCHWEIZ/SUISSE/SVIZZE RA
34	DEB	RHEINLAND-PFALZ	85	IE	IRELAND	136	PLZ	EXTRA-REGIO	187	CH01	Région lémanique
35	DEC	SAARLAND	86	IE01	Border, Midland and Western	137	PT	PORTUGAL	188	CH02	Espace Mittelland
36	DED	SACHSEN	87	IE02	Southern and Eastern	138	PT1	CONTINENTE	189	CH03	Nordwestschweiz
37	DEE	SACHSEN-ANHALT	88	IEZ	EXTRA-REGIO	139	PT2	Região Autónoma dos Açores	190	CH04	Zürich
38	DEF	SCHLESWIG-HOLSTEIN	89	IT	ITALIA	140	PT3	Região Autónoma da Madeira	191	CH05	Ostschweiz
39	DEG	THÜRINGEN	90	ITC	NORD-OVEST	141	PTZ	EXTRA-REGIO	192	CH06	Zentralschweiz
40	DEZ	EXTRA-REGIO	91	ITD	NORD-EST	142	SE	SVERIGE	193	CH07	Ticino
41	DK	DANMARK	92	ITE	CENTRO (I)	143	SE01	Stockholm	194	CHZ	EXTRA-REGIO
42	DK0	DANMARK	93	ITF	SUD	144	SE02	Östra Mellansverige	195	NO	NORGE
43	DKZ	EXTRA-REGIO	94	ITG	ISOLE	145	SE04	Sydsverige	196	NO01	Oslo og Akershus
44	EE	EESTI	95	ITZ	EXTRA-REGIO	146	SE06	Norra Mellansverige	197	NO02	Hedmark og Oppland
45	EE0	EESTI	96	LT	LIETUVA	147	SE07	Mellersta Norrland	198	NO03	Sør-Østlandet
46	EEZ	EXTRA-REGIO	97	LT001	Alytaus apskritis	148	SE08	Övre Norrland	199	NO04	Agder og Rogaland
47	ES	ESPAÑA	98	LT002	Kauno apskritis	149	SE09	Småland med öarna	200	NO05	Vestlandet
48	ES1	NOROESTE	99	LT003	Klaipėdos apskritis	150	SE0A	Västssverige	201	NO06	Trøndelag
49	ES2	NORESTE	100	LT004	Marijampoles apskritis	151	SEZ	EXTRA-REGIO	202	NO07	Nord-Norge
50	ES3	COMUNIDAD DE MADRID	101	LT005	Panevezio apskritis	152	SI	SLOVENIJA			
51	ES4	CENTRO (E)	102	LT006	Siauliu apskritis	153	SI001	Pomurska			

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