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The Evolution of Specialization in the EU15 Knowledge Space

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ABSTRACT Significant attention has been directed to processes of knowledge production in a spatial context, but little consideration has been given to the type of technological knowledge produced within specific places. In this paper we use patent co-classification data from the European Patent Office (EPO) to measure the distance between all pairs of 629 International Patent Classification (IPC) categories. A multi-dimensional scaling algorithm allows us to visualize these distances in a map of the EU15 knowledge space. We trace the evolution of that space from 1981 to 2005. The patent class distance data are combined with counts of patents by IPC categories to measure the average relatedness (specialization) of knowledge produced within each NUTS2 region. We show that knowledge specialization has increased significantly across EU15 regions over time and we report those regions that have the most specialized and the least specialized knowledge bases. Changes in the average relatedness of regional knowledge cores are decomposed to reveal the contributions of technological entry, exit and selection processes over space and time. In a final section of the paper, technological diversification and abandonment at the NUTS2 level are modeled as a function of proximity to the knowledge core of the region and to knowledge spillovers from neighboring regions that are mediated by social and spatial distance.

JEL CODES: O33, O52, R12

KEYWORDS: Evolutionary Economic Geography, Geography of Invention, Technological Change, Technology/Knowledge Space, Patent Data Analysis, Entry/Exit/Selection, Decomposition Analysis

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1. INTRODUCTION

In this paper we map the changing structure of knowledge production within 15 member states of the European Union (EU15) over the period 1981 to 2005. We are particularly interested in whether European integration has led to increasing technological specialization at the NUTS2 regional-level. An increase in the specialization of knowledge production across EU regions might signal the emergence of a European market for technology, a deepening spatial division of labor in R&D and attendant gains in the efficiency of invention and innovation. Though there has been considerable interest in the relationship between European market integration and the geographical redistribution of economic activity (Krugman and Venables 1996), this has not typically focused on the production of knowledge. A recent related literature on “smart specialization” in the EU is more explicitly directed toward knowledge-based regional policy (McCann and Ortega-Argilés 2013).

Our focus on the regional specialization of knowledge production reflects the central role that concentration plays in regulating economic performance (Marshall 1890; Duranton and Puga 2004), the resilience of regional economies (Hassink 2010; Martin 2012; Balland et al. 2014) and trajectories of economic and technological development in space (Hidalgo et al. 2007; Boschma et al. 2013; Rigby 2013; Boschma et al. 2015). We study the European Union because the knowledge structure of this aggregate economic space has not yet been mapped. At the core of our work is a relatively new method of measuring the relatedness or the distance between technology types. This method overcomes the failure of the Herfindahl Index (with categorical data) to explicitly consider variations in the “distances” between the categories over which specialization is computed. As we have done elsewhere, we urge abandonment of the Herfindahl whenever possible.

The paper is divided into six following sections. Section 2 outlines our rationale for focusing on technological specialization. We offer a brief review of the existing literature and develop a series of core arguments related to specialization and knowledge production. In Section 3, attention shifts to the use of patents as indicators of the history and geography of invention. Patent co-classification data from the European Patent Office (EPO) are used to calculate the technological distances between all patents across the EU15 for five-year periods from 1981 to 2005. Patents are shown to mass around different technologies over time and this allows us to visualize the evolution of the EU15 knowledge space. Analysis reveals that the technological relatedness, or specialization, of EU15 patents has been increasing since the early 1980s. Section 4 explores shifts in the geography of technological specialization across NUTS2 regions for different periods. Changes in regional technological specialization are driven by local variations in the relative importance of incumbent technology classes, by diversification into new technology classes and through technological abandonment. In Section 5 of the paper, we decompose changes in technological specialization within NUTS2 regions into these components and reveal how entry and exit impact the growing specialization of technology across NUTS2 regions. Section 6 estimates an exploratory model of technological entry and exit built around the influence of technological, social and geographical proximity. Section 7 offers a brief conclusion.

2. SPECIALIZATION AND THE EVOLUTION OF THE KNOWLEDGE SPACE

The spatial distributions of industries within Europe are much more dispersed compared to industrial location patterns in the United States (Krugman and Venables, 1996). Historically, national markets and interests, reinforced by language and cultural barriers have created economic landscapes across member states of the European Union (EU) that are much less distinctive than we would anticipate within an integrated economic space. Differences in geographies of industrial composition are linked to the potential returns from agglomeration economies and to lower levels of industrial productivity across much of Europe in relation to the United States (Ortega-Argilés, 2012). While the benefits of industrial and technological specialization on urban and regional economic growth have long been known (Marshall, 1890; Chinitz, 1961, Jacobs, 1969, Glaeser et al., 1992; Duranton and Puga, 2004), European geo-political and market forces limited pan-European consolidation and the emergence of specialized industry clusters similar to those of Detroit or Silicon Valley. With increasing integration, Krugman (1991) and others have predicted increases in the geographic concentration of economic activity across the European Union.

To date, evidence about levels of industrial specialization across European countries is mixed (Amiti, 1999). A multiplicity of scales of analysis (from countries to sub-national regions) and measures (absolute or relative) has made it difficult to identify a common signal in the data presented (Cutrini, 2010) or even the direction of change (Aiginer and Rossi-Hansberg, 2006). Nonetheless, some such as Greenaway and Hine (1991) have argued that the data indicate a gradual increase in national patterns of industrial specialization since the early 1980s. Midelfart-Knarvik et al. (2002) argue that we see similar trends within regions at the sub-national level, though De Robertis (2001) and Suedekum (2006) remain more agnostic. Brülhart (1998) also suggests greater geographical concentration of industry sectors across EU countries, though more recently noting substantial variations in the magnitude and even the direction of such change (Brülhart and Traeger, 2005). Ezcurra et al. (2006) present evidence that the spatial concentration of manufacturing industries across European regions accelerated as the European Single Act came into force. Ortega-Argilés (2012) suggests that a widening of the productivity gap between the United States and the EU since the mid-1990s is underpinned by a lack of specialization in Europe that limits the potential benefits of technological linkages and spillovers between both between sectors and regions.

In order to close the productivity gap with the United States, and to foster a more innovation-friendly environment in the EU, a number of policy instruments have been put in place. The European Framework programmes, part of the larger European Research Area (ERA) initiative, is one example. More recently the Innovation Union programme, a Europe 2020 project headed by the European Commission, is another attempt to enhance innovation in the heterogeneous economic environment of EU regions. A key element of this endeavor is the smart specialization concept (Foray and Van Ark, 2007; McCann and Ortega-Argilés, 2013). Promoting a logic that can be applied to a variety of regional settings, smart specialization emphasizes local context and structural evolution as central components of incremental and radical social, political and economic transformation (Foray et al., 2011). A particular focus is directed towards science and technology domains and their properties in terms of size and connectedness (Foray et al., 2009). In order to develop a competitive innovation strategy, it is suggested that regions need to identify their core competencies, as well as the potential for complementarities within their respective knowledge base. David et al. (2009) argue that in order to observe and implement the smart specialization concept there is a need for alternative indicators that provide a better understanding of high-technology and knowledge intensive sectors and the synergies that exist between them. Patent data, capturing the development of novel products and processes of economic value, are particularly useful in this regard.

Indeed, patent data have been used to explore patterns of specialization in invention and innovation using the technology codes within which patents are classified. Thus, Paci and Usai (2000), Anderson and Ejermo (2008), Fleming et al. (2007) and Lobo and Strumsky (2008), link measures of technological concentration to the productivity of invention at a variety of spatial scales. Patent data also have been used to measure the connectedness between different technology classes using citations (Leten et al., 2007) and co-classification frequencies, primarily to explore the cohesion of technologies within firms (Jaffe, 1986; Verspagen, 1997, Breschi et al., 2003). Graf (2006), Quatraro (2010), Kogler et al. (2013) and Rigby (2013) extend these techniques to explore the geographical dimensions of technological specialization. To date, the knowledge space of the European Union and its constituent regions have not been mapped using patent data. A first order of business, then, is to explore the structure of technology in the EU15 and to measure the coherence or the specialization of knowledge cores across NUTS2 regions.

Over the relatively long period of time that we explore the technological characteristics of NUTS2 regions in Europe, there has been considerable change. Evolutionary accounts of aggregate economic dynamics rest heavily on population models (Hannan and Freeman 1977) that decompose the movements of key variables into effects that are linked to processes of entry, exit and selection. There has been much recent work tracing technological, occupational and industrial diversification (entry) and abandonment (exit) at the regional level since the pioneering paper by Hidalgo et al., (2007). Although concerns with endogeneity in much of this work remain, industrial branching within regions is closely linked to the structure, or the relatedness, of local economic activity (Boschma and Frenken 2011; Neffke et al., 2011; Boschma et al., 2013). Rigby (2013) extends these arguments to capture the influence of neighboring regions.

Just as important as entry and exit dynamics to the evolution of technological specialization within regions are changes in cognitive proximity or relatedness between technology types. Connections between technologies emerge and wither through creative destruction, by invention, recombination and a continual remapping of linkages between technologies driven by competition (Kauffman, 1993; Weitzman, 1998; Olsson, 2000). This remapping of the relationships between knowledge subsets is linked to trajectories of search and development (Clark, 1975; Dosi, 1982), to broader ecologies of technologies (Podolny and Stuart, 1995; Carnabuci, 2010), to shifting recombinant possibilities (Valverde et al., 2007), identification of critical inventions (Martinelli and Nomaler, 2014) and branching points in technological evolution (Verspagen, 1997). As the topology of knowledge space changes, so the possibilities for smart specialization are reworked. We show how changes in the structure of knowledge space impact changes in technological specialization across regions of the EU15.

While this discussion highlights the role of technological proximity in shaping the dynamics of knowledge development within and across regions, it should be clear that such development occurs within a social and political order that is largely constitutive of market relationships and broadly shaped by them. Within economic geography, the co-evolution of institutions and technologies is only just beginning to receive the attention it deserves (Hall and Soskice 2001, Martin 2010, Boschma and Capone 2014).

3. EU15 Knowledge Space and Patterns of Technological Specialization

The use of patent data to capture the production of knowledge dates back more than half a century (Schmookler, 1962, 1966; Scherer, 1965). There has been a steady increase in the volume and impact of studies that utilize patent data to analyze innovation and the flow of knowledge (Griliches, 1984; Scherer, 1984, Jaffe et al., 1993; Jaffe and Trajtenberg, 2002). Though the shortcomings of patent data are reasonably well-known (Pavitt, 1985; Griliches, 1990; Schmoch, 1999), they are increasingly used in more sophisticated ways to track the movement of knowledge and inventors (Jaffe et al., 1993; Fischer et al., 2006), inventor collaboration (Breschi and Lissoni, 2004; Singh, 2005), the complexity of knowledge (Fleming and Sorenson, 2001; Balland and Rigby, 2014) and the value of inventions (Harhoff et al., 2003).

Despite these efforts very little is known about the character of knowledge produced in specific places and how the structure of knowledge bases move over time. Recent work has mapped the changing structure of the U.S. 'knowledge space' and explored shifts in the nature of knowledge generated within a small sample of U.S. cities (Kogler et al., 2013; Rigby, 2013). However, with the exception of early work by Graf (2007), we know very little about the structure of the European knowledge space. One of the main reasons for this has been the absence of comprehensive, standardized and disambiguated patent data for Europe. Fortunately, these data are now becoming available, based on European Patent Office (EPO) records. The data employed in the present investigation derive from the EP-INV database produced by CESPRI-Università Bocconi (Coffano and Tarasconi, 2014; Pezzoni et al., 2014)[1].

There are relatively few records in this database that pre-date 1980, thus our analysis begins in the 5-year period 1981-5 and it ends in the period 2001-05. Five-year periods are employed to smooth annual fluctuations in patent applications for approximately 213 NUTS2 regions and 629 International Patent Classification (IPC) codes. The IPC codes demarcate subsets of knowledge in the EPO data. We use these codes to reference distinct technologies. The NUTS2 regions and IPC technology codes have changed repeatedly over time. We use a consistent set of regional codes for the year 2006 along with IPC classes demarcated in IPC 2012.01. We focus on regions of the EU15 rather than newer versions of the EU to maximize the length of the study period.

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[1] The data employed in the present investigation were generously made available to us through Francesco Lissoni (GREThA, Université de Bordeaux & CRIOS – U Università L.Bocconi). We gratefully acknowledge the initial help in setting up our version of the database, and then the ongoing data support throughout the duration of this project of both, Francesco Lissoni and Gianluca Tarasconi (KITeS – Università L.Bocconi).

The EPO provides information on each utility patent application including the year of application, the inventor or co-inventors of the patent and the knowledge (IPC) classes into which the patent is placed. Our focus is on year of application, i.e. priority year, rather than patent grant year due to the time-lag from the date of invention and filing to grant date. Patents are allocated to one or more IPC classes according to the knowledge claims they make. Almost all patents, more than 99%, make claims to fewer than 20 IPC classes. We distribute individual patents across IPC classes on the basis of the share of knowledge claims within each class. The location of inventors is used to locate a patent geographically.

The EPO data are different from U.S. patent data in that a primary inventor and thus a primary location are not attributed to EPO patents with multiple inventors. This complicates identification of the geographical location of EPO patents. To geo-locate EPO patents produced by multiple inventors we make use of address data for each co-inventor and fractionally split patents across NUTS2 regions on the basis of the share of co-inventors located in each of those regions. The contribution of non-EU15 co-inventors is removed in the first stage of analysis. Thus, if a single EPO patent has three co-inventors, one living in Los Angeles, a second in Dublin and a third in London, that patent is given an EU15 weight of two-thirds and then one-third of that patent is allocated to Dublin and one-third to London. Further, assume that the patent makes four knowledge claims, one in class A23B, one in class A23C and two in class A44C. Unfortunately, there is no straightforward way of identifying the knowledge generated on a patent by individual co-inventors. Thus, it is assumed here that all inventors add the same technological information on each patent. With our EU15 patent developed in LA, Dublin and London, the two-thirds EU15 weight of the patent is further divided into the three knowledge classes listed such that (1/4)(1/3) of the patent is assigned to knowledge class A23B in Dublin, (1/4)(1/3) to class A23C in Dublin and (2/4)(1/3) to class A44C in Dublin. The same shares of the patent are also allocated to the same knowledge classes in London. Thus, the technology class and locational shares of an individual patent sum to the patent's overall EU15 weight. That weight is one if all co-inventors are located in the EU15, zero if all co-inventors are located outside the EU15, and somewhere between these limits otherwise. In this way, as much information as possible is utilized from the EPO records, while all EU15 knowledge production is counted and weighted consistently.

Table 1 shows the number of EU15 patent applications for the five-year periods examined. The simple count of patents (column 2) tracks patent applications to the EPO regardless of the origin of inventors. The patent counts in column 3 of the table are weighted by the share of EU15 co-inventors. The ratio of patent counts in columns 3 and 2 of Table 1 illustrates the average share of EU15 inventors found on patent applications processed by the EPO: that share has monotonically declined from 98.6% in 1981-85 to 95.6% in 2001-05. Table 1 also reports the average number of knowledge claims made by patents over time. Knowledge claims are placed into one of 629 primary IPC classes by the EPO. The number of primary classes found on EPO patents increases from an average of 1.83 in 1981-85 to 1.94 in 1996-2000. (A reduction in the average number of patent classes by 2005 is a consequence of changes in the International patent Classification system.) An individual primary class may appear more than once on a single patent, reflecting knowledge claims in different sub-categories of a primary class. The total number of knowledge claims on patents also has increased over time, from 3.66 in 1981-85 to 4.20 in 1996-2000.

EU15 Knowledge Space

An EU15 knowledge space is constructed for 1981-85, 1991-95 and 2001-05 using co-class information gathered from individual patents, following the earlier work of Jaffe (1986), Engelsman and van Raan (1994), Verspagen (1997), Breschi et al. (2003) and others. The number of primary patent classes on which we focus is considerably larger than that employed in most prior studies and thus the knowledge space outlined here is of higher resolution than those reported to date.

Table 1: EPO Patent Characteristics

YEARS	NUMBER OF PATENTS (simple count)	NUMBER OF PATENTS (EU15-weighted)	AVERAGE NUMBER OF CO-CLASSES PER PATENT	
			Single count	Multiple count
1981-85	89,533	88,268.9	1.830	3.658
1986-90	130,746	128,222.4	1.896	3.871
1991-95	144,249	140,265.0	1.956	4.092
1996-00	227,326	218,848.2	1.944	4.199
2001-05	272,072	260,188.0	1.788	3.516

Note: The number of patents in any period is fixed by the number of patent applications in that period. The number of patents (simple count) refers to those patent applications made to the EPO by inventors regardless of location. The EU15 patent count only includes patents where at least one co-inventor is located within an EU15 member nation. Patents are weighted by the EU15 share of all inventors. Single count only counts a primary class once on each patent regardless of how many times a primary class actually appears together with different sub-classes. Multiple count records the total number of times each primary class appears on a single patent, indicating a patent introduces novelty into a number of sub-classes within each of the primary classes or that makes more than one claim in a particular class.

To measure the proximity, or technological relatedness, of patent classes we use the distribution of knowledge claims by IPC class on each patent. This is typically done by counting the number of patents for a given period that contain a co-class pair, say *i* and *j*, and then standardizing this count by the number of patents in total that record knowledge claims in IPC classes *i* and *j*. There are two problems with this method. First, it weights patents unequally, giving more weight to patents that contain a larger number of knowledge classes. Second, it cannot discriminate between individual patents that contain uneven numbers of knowledge claims across a common set of classes. For example, suppose that one patent records four separate knowledge claims in IPC class H02J and one knowledge claim in IPC class H02B (i.e. H02J, H02J, H02J, H02J, H02B). This patent would look identical to another that contained one knowledge claim in each class (i.e. H02J, H02B). We propose a method of calculating technological proximity that weights each EU15 patent uniformly and that distinguishes between all the knowledge characteristics/claims that are found on the patent record.

To operationalize this method, the first step is to count the number of knowledge claims on each patent, n_p, regardless of how many knowledge classes the claims are distributed across. Each knowledge class claim is given the weight $1/n_p$ such that the total weight of claims on an individual patent equals one. The second step is to record the IPC class of each of these knowledge claims. The number of knowledge claims on patent *p* in IPC class *i*, where *i* = 1, …, 629, is given as n_{ip}. Then, the number of knowledge claims in technology (IPC) class *i* on all patents in a specific period is

$$\sum_p n_{ip} \frac{1}{n_p} = \sum_p \frac{n_{ip}}{n_p}$$

and this is equal to the overall number of patents in technology class *i* (P_i). The total number of patents in the same period is

$$\sum_i \sum_p \frac{n_{ip}}{n_p} = \sum_i P_i = P.$$

The number of pairwise co-class links across all the knowledge claims on patent *p* is $l_p = \left(n_{ip} * (n_{ip} - 1)\right)/2$. The third step in this technique is to count the links that join knowledge claims, recording the IPC classes of the claims linked. Each pairwise link for a single patent is given the weight $1/l_p$ so that the sum of link weights for patents with more than a single knowledge claim is one. The number of links between patent class claims *i* and *j* on patent *p* is n_{ijp}, where *i* and *j* range in value from 1 to 629. To illustrate these measures, take again the patent outlined above with knowledge claims H02J, H02J, H02J, H02J, H02B. For this patent, $n_p = 5, n_{H02J\,p} = 4, n_{H02B\,p} = 1, l_p = 10$, $n_{H02B\,H02J\,p} = 4, n_{H02J\,H02J\,p} = 6$.

Repeating these measures across all patents in a given period yields weighted counts of the number of co-class links between all pairs of knowledge classes $\sum_i \sum_j \sum_p \frac{n_{ijp}}{l_p} = L_{ij}$. The co-class counts are influenced by the number of patents found within each individual patent class. Therefore, the final step in estimating the average relatedness between two patent technology classes (IPCs) is to standardize the co-class link counts by the square root of the product of the number of patents in the respective technology classes. Different methods of standardization are discussed by van Eck and Waltman (2009). We prefer this simple form of standardization for the reasons outlined by Joo and Kim (2010). Thus,

$$S_{ij} = \frac{L_{ij}}{\sqrt{P_i * P_j}},$$

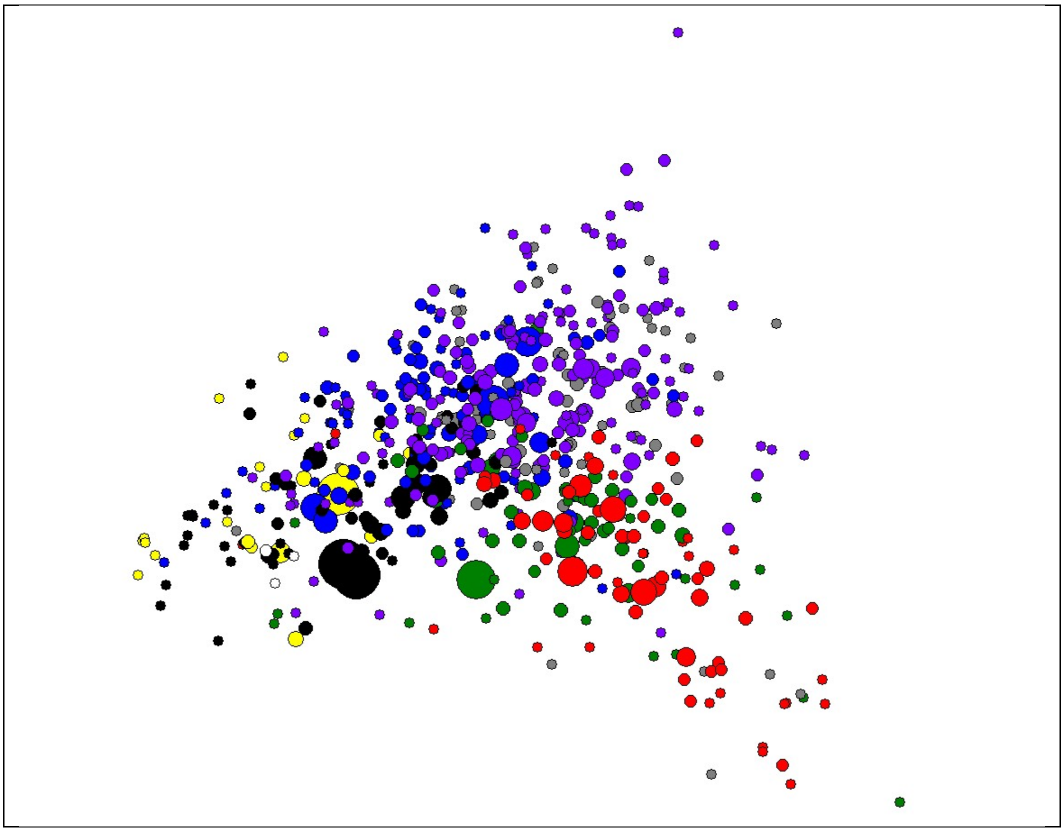
where S_{ij} is an element of the standardized co-occurrence matrix (***S***) that indicates the technological proximity, or relatedness, between all pairs of patent classes in a given period. The elements on the principal diagonal of ***S*** are set to 1.

The 629 primary technology classes reported by the EPO have been aggregated into seven broad technology classes on the basis of a shared core of knowledge. We anticipate that primary technology classes within the aggregate technology groups should exhibit relatively high technological relatedness measures with one another. That is, technological relatedness should be higher between primary technology classes that share a common base of knowledge than between primary technology classes that do not share a common knowledge core.

With the aid of UCINET (Borgatti *et al*. 2002), the network of technological relatedness across the 629 primary patent classes is mapped. The technological relatedness network is generated with the Gower-scaling metric, itself derived to examine patterns of similarity across network nodes (Gower 1971). The nodes in the network correspond to each of the 629 distinct technological classes within the EPO. A handful of isolates are deleted. The relative positions of the nodes are fixed by the values in the symmetric standardized co-occurrence matrix (***S***). The principal diagonal of that matrix plays no role in the relative locations of the nodes. The knowledge relatedness networks for 1981-85, 1991-95 and 2001-05 are shown below (see Figure 1).

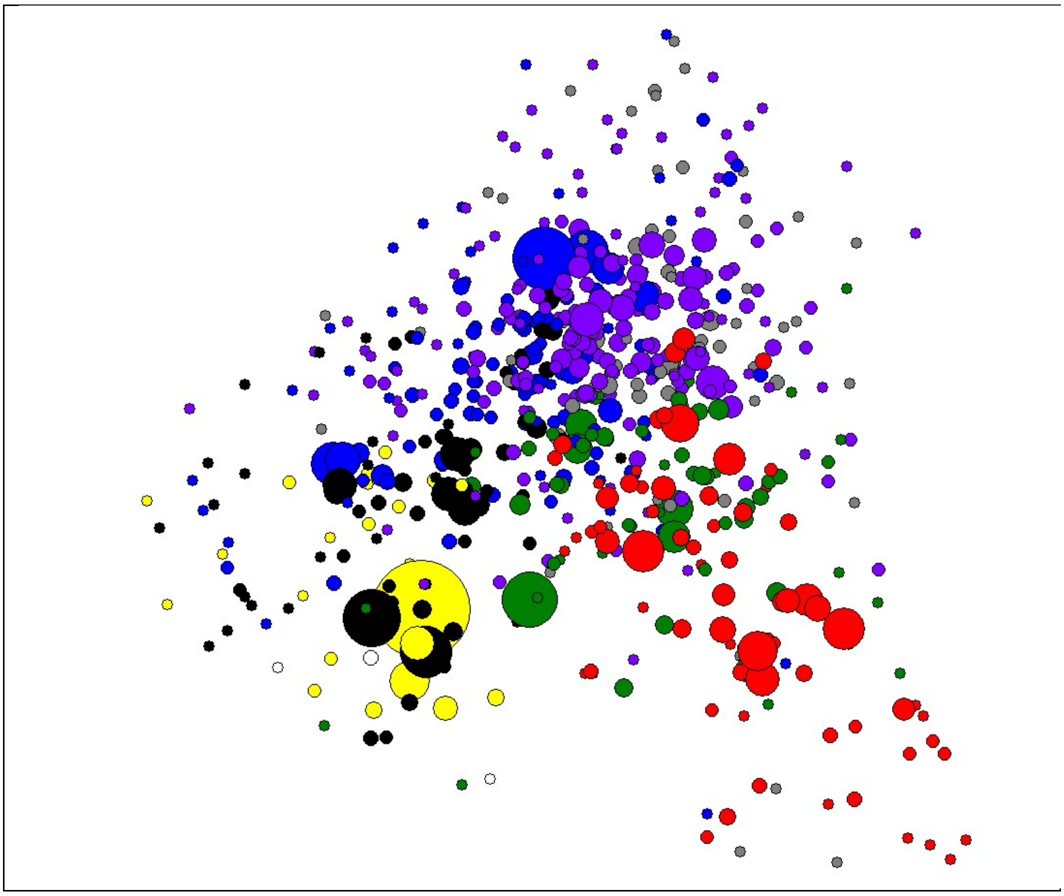
Figure 1: EU15 Knowledge Space

a. 1981-85

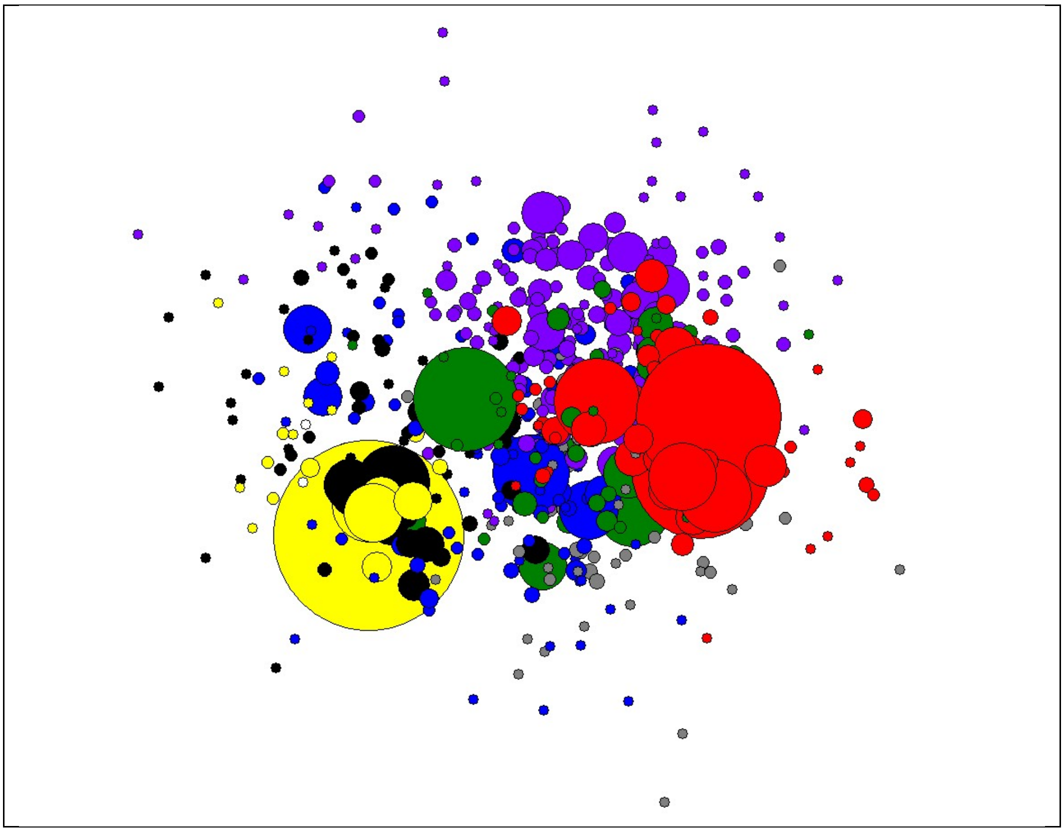


Notes: Red = Electronics (1), Green = Instruments (2), Black = Chemicals (3), Yellow = Drugs & Medicine (4), Blue = Industrial Process (5), Purple = Machinery & Transport (6), Grey = Consumer Goods (7). The nodes are sized according to the number of patents and the sizing is consistent over time. The largest patent class in 2001-05 (A61K = Preparations for medical, dental or toilet purposes) contains 10,360 patents.

b. 1991-95



c. 2001-05



There is clear evidence of the clustering of individual patent categories within the aggregate classes of Figure 1, indicating that the relatedness measure is capturing what may be considered a common knowledge base within the more aggregate technology groupings. The size of each node illustrates the number of patents in that technology class in the given period. Node sizes have been scaled to allow comparison over time. Over the past twenty-five years or so, there has been a marked increase in the relative frequency of patents in those classes that we associate with newer technologies such as drugs and medicine, in electronics and instruments. There appears to be some overlap of the knowledge bases of drug and medical patents with chemicals patents, and electronic patents with those in the instruments sector. Patents in the machinery and transport and consumer goods groups are somewhat more dispersed.

To generate a better idea of the clustering of patents in the EU15 knowledge space, the average technological relatedness (proximity) between all pairs of patents is calculated. A higher average relatedness score indicates that patents are located in technology classes that are relatively close to one another in the EU15 knowledge space. These are the technology classes that tend to co-occur with relatively high frequency on individual patents. A lower relatedness score would indicate that patents are distributed over technology classes that are, on average, further apart from one another in knowledge space. Average relatedness provides a useful summary measure of technological specialization, one much more accurate than could be generated by an index such as the Herfindahl that ignores the variance in inter-class distances of categorical variables.

The average relatedness value for all patents in time period *t* is calculated as:

$$AR^t = \frac{\sum_i \sum_j S_{ij}^t \, D_{ij}^t}{P^t * (P^t - 1)}$$

where S_{ij}^t represents the technological relatedness between patents in technology classes *i* and *j*, P^t is a count of the total number of patents in year *t*, and where D_{ij}^t $(= (P_i^t + P_j^t)(P_i^t + P_j^t - 1))$ counts the number of links between all pairs of patents that can be located in technology classes *i* and *j* in year *t*. This measure of average relatedness is easily adapted to focus on particular subsets of technology classes or regions. Table 2 provides information on average technological relatedness, or specialization, between all patents in the EU15 knowledge network and between patents within each of the seven aggregate technology fields. Overall, average relatedness increased by approximately 35% during the period examined. Thus, over time, more patents are being generated that embody technological claims that are closer to one another in knowledge space. This is consistent with the growth of technological specialization, an increase in the shared knowledge base that underpins invention.

Table 2 reports how technological specialization varies across major patent classes and how specialization has changed over time. Note that average relatedness values overall are not a simple average of those within each of the patent groupings, for this average ignores the lower levels of technological proximity found between individual IPCs in different aggregate groups. On average, technological relatedness, or proximity, is significantly higher in the drugs and medicine group than in the other IPC aggregates. This reflects the relatively small number of individual patent classes in this group, the proximity of those classes in knowledge space and the clustering of patents in relatively few drug-related IPCs. The electronics, instruments and chemicals groups all show technological proximity higher than average, while industrial process, consumer, and especially the machinery and transport groups all report technological proximity that is lower than average. The electronics group of IPCs records the largest gain (56%) in technological proximity over the period examined. The instruments and drugs and medicine groups follow, with reported gains in proximity between patents of around 22%. The chemicals sector is the only aggregate group to register a slight decline in technological proximity over time.

Table 2: Average Technological Relatedness by Major Patent Class, EU15 Total

PATENT GROUP	YEAR				
	1981-85	1986-90	1991-95	1996-00	2001-05
ELECTRONICS	0.0451 (14,197.0)[1]	0.00453 (20,558.4)	0.0473 (25,017.1)	0.0589 (50,860.2)	0.0705 (62,017.5)
INSTRUMENTS	0.0535 (11,988.4)	0.0548 (17,471.9)	0.0544 (18,727.3)	0.0604 (29,006.6)	0.0654 (35,954.3)
CHEMICALS	0.0780 (15,956.2)	0.0719 (21,030.0)	0.0694 (20,836.6)	0.0629 (24,843.4)	0.0665 (26,694.7)
DRUGS & MEDICINE	0.2899 (4,489.3)	0.2990 (8,513.5)	0.3364 (10,788.6)	0.3499 (19,701.8)	0.3474 (25,053.8)
INDUSTRIAL PROCESS	0.0408 (15,522.0)	0.0421 (23,542.8)	0.0444 (25,184.7)	0.0428 (32,811.1)	0.0430 (35,909.6)
MACHINERY & TRANSPORT	0.0166 (21,647.2)	0.0175 (30,462.5)	0.0181 (32,373.0)	0.0198 (50,853.8)	0.0203 (61,721.6)
CONSUMER	0.0354 (4,589.5)	0.0382 (6,822.6)	0.0391 (7,476.2)	0.0402 (10,988.8)	0.0417 (13,100.3)
TOTAL	0.0095 (88,268.9)	0.0097 (128,222.4)	0.0102 (140,265.0)	0.0115 (218,848.2)	0.0129 (260,188.0)

Note: Number of (EU15-weighted) patents are shown in parentheses. Column totals might vary because of rounding.

4. THE GEOGRAPHY OF INVENTION AND REGIONAL SPECIALIZATION

The geography of invention across NUTS2 regions within the EU15, as represented by patents, is highly uneven. Moreno et al. (2005) and Usai (2011) have already reported this geography, like us using fractional patent shares in cases where co-inventors are located in different regions. However, that geography is remarkably stable over time. The correlation coefficient between patent counts by region for the periods 1981-85 and 2001-05 is 0.93. It is even higher for consecutive time-periods. Table 3 provides a snapshot of the geography of EU15 patenting, reporting the twenty most and least inventive regions at the start and end of the time period we examine. We have not standardized these counts by region size. The median number of patents produced across EU15 regions has risen from 161 in 1981-85 to 521 in 2001-05. There has been some tightening in the distribution of patents across the regions, with the coefficient of variation declining from 2.07 to 1.73 between 1981-85 and 2001-05.

Table 3: Regional Inventiveness as Measured by Patent Output in 1981-1985 and 2001-2005

Rank	NUTS2	Region	1981-85	Rank	NUTS2	Region	2001-05
1	FR10	Ile de France	7,745	**1**	FR10	Ile de France	15,312
2	DE21	Oberbayern	4,966	**2**	DE11	Stuttgart	13,050
3	DE71	Darmstadt	4,207	**3**	DE21	Oberbayern	12,198
4	DEA1	Dusseldorf	3,741	**4**	NL41	Noord-Brabant	9,749
5	DEA2	Koln	3,714	**5**	DE71	Darmstadt	7,361
6	DE11	Stuttgart	2,981	**6**	DEA2	Koln	7,315
7	FR71	Rhone-Alpes	2,226	**7**	ITC4	Lombardia	7,032
8	DE12	Karlsruhe	2,130	**8**	DEA1	Dusseldorf	6,961
9	NL41	Noord-Brabant	2,090	**9**	DE12	Karlsruhe	6,768
10	DEB3	Rheinhessen-Pfalz	2,073	**10**	FR71	Rhone-Alpes	6,510
11	ITC4	Lombardia	1,912	**11**	DE13	Freiburg	4,908
12	DE25	Mittelfranken	1,497	**12**	DE14	Tubingen	4,387
13	DE13	Freiburg	1,426	**13**	DEB3	Rheinhessen-Pfalz	4,211
14	DEA5	Arnsberg	1,296	**14**	FI18	Etela-Suomi	4,021
15	UKJ2	Surrey, E&W Sussex	1,260	**15**	DE25	Mittelfranken	3,956
16	SE11	Stockholm	1,198	**16**	ITD5	Emilia-Romagna	3,607
17	UKJ1	Berks, Bucks & Oxon	1,120	**17**	DEA5	Arnsberg	3,483
18	DE14	Tubingen	1,003	**18**	SE11	Stockholm	3,055
19	ITC1	Piemonte	987	**19**	DE30	Berlin	2,982
20	UKI2	Outer London	896	**20**	DK01	Hovedstaden	2,860
:	:	:	:	**:**	:	:	:
170	DED3	Leipzig	9	**170**	NL34	Zeeland	106
171	NL23	Flevoland	9	**171**	NL23	Flevoland	105
172	ITD2	Provincia Autonoma Trento	8	**172**	SE32	Mellersta Norrland	105
173	ES13	Cantabria	6	**173**	UKK3	Cornwall and Isles of Scilly	98
174	IE01	Border, Midland and Western	6	**174**	PT17	Lisboa	94
175	ES11	Galicia	6	**175**	AT11	Burgenland (A)	86
176	ES24	Aragon	5	**176**	PT11	Norte	78
177	ITC2	Valle d'Aosta/Vallee d'Aoste	5	**177**	UKM6	Highlands and Islands	74
178	UKM6	Highlands and Islands	5	**178**	ITG2	Sardegna	69
179	DE80	Mecklenburg-Vorpommern	4	**179**	ES42	Castilla-La Mancha	68
180	GR12	Kentriki Makedonia	4	**180**	GR12	Kentriki Makedonia	65
181	ES42	Castilla-La Mancha	4	**181**	ITF6	Calabria	57
182	ES41	Castilla y Leon	4	**182**	ES12	Principado de Asturias	52
183	ITF5	Basilicata	3	**183**	ES62	Region de Murcia	42
184	ES70	Canarias	2	**184**	ES70	Canarias	33
185	ES12	Principado de Asturias	2	**185**	PT16	Centro (P)	31
186	ES53	Illes Balears	2	**186**	ITF5	Basilicata	23
187	ES62	Region de Murcia	2	**187**	ES13	Cantabria	23
188	PT11	Norte	0	**188**	ITC2	Valle d'Aosta/Vallee d'Aoste	22
189	PT16	Centro (P)	0	**189**	ES53	Illes Balears	22

Note: Inventor counts are based on fractional shares per patent. For example, if a patent was developed by three inventors residing in the very same NUTS region each of these inventors will be allocated a count of one-third.

Although overall the geography of invention is relatively stable within the EU15, a number of regions have significantly shifted their rank positions over time. The regions that have dropped most in the patent rankings since 1981 are all located within the UK. The regions that have moved up in rankings most sharply since 1981 are West Finland, Catalonia and three German regions centered on Thüringen, Dresden and Brandenburg.

Of most interest in this paper is how the different NUTS2 regions within the EU15 have performed in terms of the relatedness of their inventions since 1981. For all regions, we measure the average technological relatedness, or specialization, of patents produced using the methodology outlined above, computing the average distance between all pairs of patents generated within each region. Limiting summary statistics to regions with more than 20 patents in the first time-period, 1981-85, technological relatedness values across the EU15 ranged from 0.006 to 0.127. The median (mean) regional relatedness score was 0.016 (0.021) for this period and the coefficient of variation was 0.714. In the second time-period, 2001-05, technological relatedness values ranged from 0.10 to 0.137. The median (mean) regional relatedness score was 0.023 (0.028) and the coefficient of variation remained at 0.714.

From 1981-85 to 2001-05, the average (mean) NUTS2 technological relatedness score increased by approximately 33% across the EU15. Overall, almost three-quarters of observed NUTS2 regions register gains in measures of technological specialization between 1981-85 and 2001-05. Figures 2 and 3 provide an overview of regional technological specialization for these two time-periods. The NUTS2 regions with the highest levels of technological specialization in 1981-85 (greater than 0.05), were N.E. Scotland, Merseyside, E. Yorkshire, Cumbria, Luxembourg, Rheinhessen-Pfalz and Kent. Note that many of the most specialized regions have relatively small numbers of patents. For the UK regions just listed, and for Luxembourg, patent counts vary from 62 to 390. Rheinhessen-Pfalz registered just over 2000 patents in the period 1981-85. The N.E. Scotland region was strongly focused on oil and gas technologies, drilling and pipes. Mersyside patents were dominated by Unilever research, mostly in detergents, and by Pilkington glass. Cumbrian patent were mostly in vehicle fittings, while those in East Yorkshire were mostly owned by BP Chemicals. The patents in Kent were largely concentrated in chemicals and medical preparations assigned to Shell, Pfizer and a number of other companies. Patenting in Luxembourg in 1981-85 was heavily concentrated in tyre technologies (Goodyear) and in iron and steel (Paul Wurth). Patents in Rheinhessen-Pfalz focused mostly in chemicals and medical preparations, the dominant assignee being BASF. The most diversified NUTS regions in terms of patents in 1981-85 were Stockholm and West Sweden, Arnsberg and Stuttgart in Germany and Île de France.

Two decades later, technological specialization in most EU15 NUTS2 regions has increased significantly (see Figure 3). Relatively high relatedness scores (>0.05) are now present in close to twenty EU15 regions. Most parts of the UK that were highly specialized in the period 1981-85 have retained their technological cohesion through 2001-05, most all in the same patent fields. A number of new NUTS2 regions have focused their knowledge production and have registered significant gains in technological relatedness.

Figure 2: Average Technological Relatedness in EU15 NUTS2 Regions, 1981-85

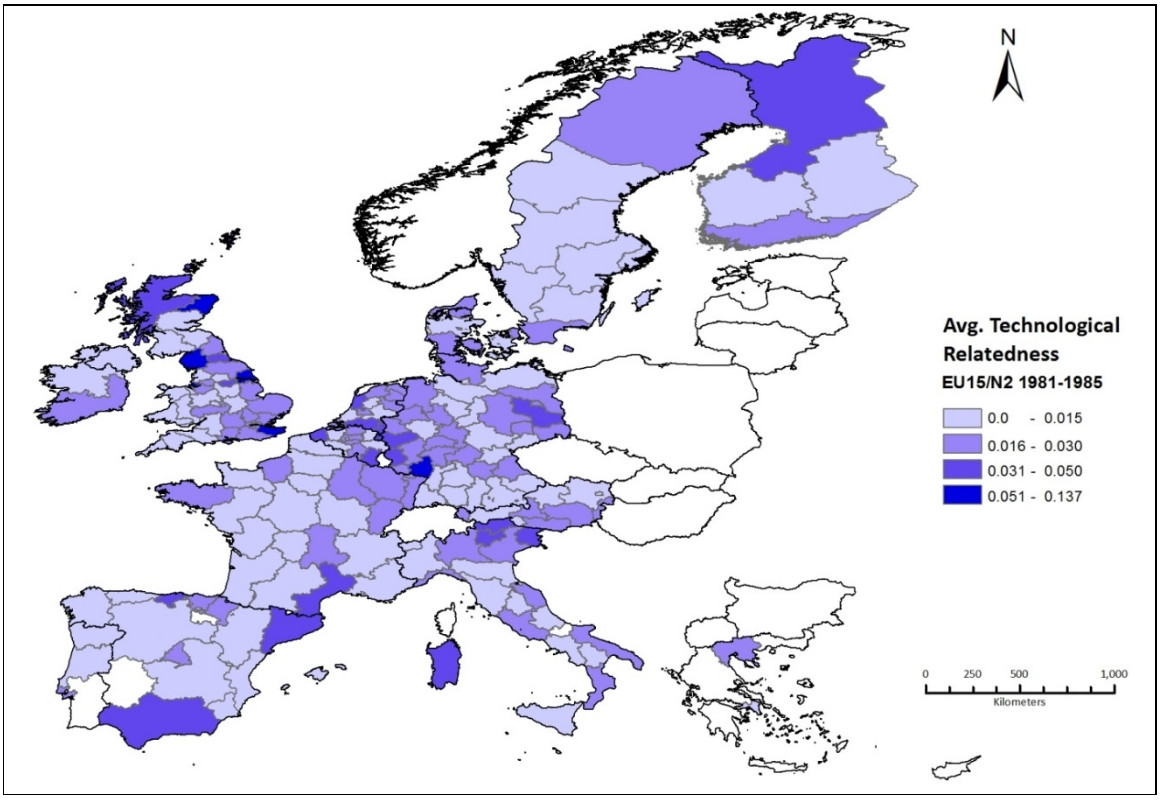
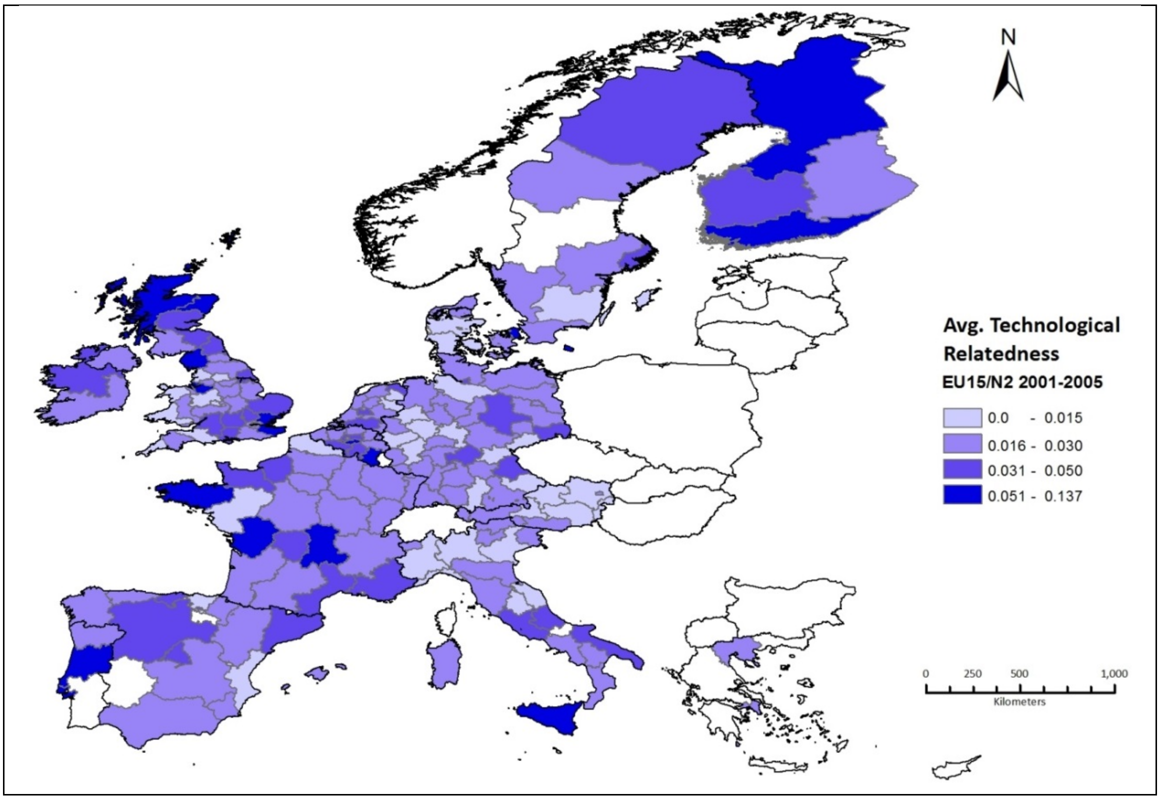


Figure 3: Average Technological Relatedness in EU15 NUTS2 Regions, 2001-05



The most prominent of these places include Northern and Southern Finland where knowledge production is focused largely on electronic circuitry and communications, and is dominated by Nokia. In France, the most technologically specialized regions in 2001-05 include Auvergne (Michelin patents), Bretagne (electronics and ICT) and Poitou-Charentes (automotive). In Germany, Hovedstaden is highly specialized in the development of medical preparations and chemical compounds. This same specialization characterizes Brabant Walloon in Belgium. In the Luxembourg region of Belgium most patents are found in tyre technologies and related automotive fields. In Portugal, the Lisbon NUTS2 region is highly specialized in medical preparations and organic compounds, and in Sicily, patent production is dominated by STMicroelectronics in the semiconductor field. The most diversified EU15 NUTS2 regions in terms of knowledge production in 2015 are Cornwall, Shropshire and Staffordshire in the UK, Schwaben, Arnsberg, Oberfranken, Luneberg and Niederbeurgen in Germany, Pays de la Loire in France, and Liguria, Marche and Veneto in Italy.

The NUTS2 regions that display the most significant increases in technological specialization after 1981-85 are Stockholm (+340%), Bretagne (+307%), Essex (+282%), Lansi-Suomi (+302%) and Provence-Alpes-Cote d'Azur and Eastern Scotland (both +240%). The regions that experienced the largest decline in technological relatedness, on the order of 50%, are Koln (Cologne), Rheinhessen-Pfalz, and Veneto.

While measures of average technological relatedness across EU15 NUTS2 regions provide some insights into geographies of specialized knowledge production and how these have shifted over the last two decades it does not account for the changes observed. In the following two sections of the paper the evolution of regional technological specialization across the EU15 is decomposed into a number of components, notably technological entry, exit, selection and incumbent effects. Models of technological entry and exit are then linked to various forms of proximity within EU15 regions.

5. Decomposing Regional Changes in Technological Specialization

Between 1981 and 2005, European regions experienced considerable growth and turnover in their knowledge bases. Out of a total of 133,977 (213x629) possible region-technology combinations, 34,005 (25.4%) existed in the period 1981-1985, increasing to 53,606 (40%) by 2001-05. In other words, regions started to fill a lot of empty technology niches over the period examined. Of the 34,005 region-technology combinations in existence in 1981-85, about 80% were still generating patents twenty years later. However, only 50% of the technology class-region pairings found in 2001-05 existed in 1981-1985. The results from the last section suggest that this general increase in the number of technology classes in which patents were developed within individual regions was not based on random assignment but rather reflected a growing specialization of invention at the regional level. So while most regions began to patent across a larger number of technology classes after 1981, on average those classes were located closer to one another in the EU15 knowledge space.

Evolutionary accounts of aggregate change suggest a series of processes - entry, exit, selection - through which resources are distributed across micro-level units. Though the individual technology classes of the International Patent Classification system might be imagined as the micro-units in our evolutionary analysis, it should be clear that those classes are not in competition with one another. However, economic agents distribute their resources across these patent classes in the hope of developing new knowledge subsets and generating technological rents. We imagine technological entry as a process through which economic agents move into patent classes that have not yet been explored within a region. Technological exit is conceived as a process where economic agents in a region abandon exploration within patent classes in which they were previously active. Selection, or differential growth, occurs when the relative level of activity within established patent classes of a particular region change over (Nelson and Winter 1982; Metcalfe 1998). In this section of the paper we explore how technological entry, exit and selection have impacted aggregate measures of technological specialization across the NUTS2 regions of the EU15 since 1981.

More formally, changes in average regional relatedness (technological specialization), can be depicted as follows. In each period *t*, technological relatedness in region *r* is given as $AR_r^t = \sum_i \sum_j x_{ijr}^t S_{ij}^t$, where S_{ij}^t is the relatedness (proximity) value between technology classes *i* and *j* at the EU-15 level and x_{ijr}^t represents the share of all possible patent to patent links within region *r* at time *t* that link technology classes *i* and *j*. In other words,

$$x_{ijr}^t = \frac{(P_{ir}^t + P_{jr}^t)(P_{ir}^t + P_{jr}^t - 1)}{\sum_i P_{ir}^t (P_{ir}^t - 1)}$$

where P_i indicates the number of patents in technology class *i*. Then, the change in technological relatedness within a region over time is given as

$$AR_r^{t+1} - AR_r^t = \sum_i \sum_j (x_{ijr}^{t+1} S_{ijr}^{t+1} - x_{ijr}^t S_{ijr}^t).$$

Following the literature on productivity decompositions[2] (Foster et al., 1998), the change in aggregate technological relatedness in region *r* between times *t* and *t+1* can then be decomposed as

$$AR_r^{t+1} - AR_r^t = \sum_{ij\in INC} \left(S_{ijr}^{t+1} - S_{ijr}^t\right) x_{ijr}^t + \sum_{ij\in INC} \left(x_{ijr}^{t+1} - x_{ijr}^t\right)\left(S_{ijr}^t - AR_r^t\right) +$$

$$\sum_{ij\in INC} \left(S_{ijr}^{t+1} - S_{ijr}^t\right)\left(x_{ijr}^{t+1} - x_{ijr}^t\right) + \sum_{ij\in N} \left(S_{ijr}^{t+1} - AR_r^t\right) x_{ijr}^{t+1} - \sum_{ij\in X} (S_{ijr}^t - AR_r^t) x_{ijr}^t$$

In the equation immediately above, the subscript *INC* denotes incumbent links, links between patents in technology classes that exist in year *t* and *t+1*, *N* represent new links to technology classes that exist in *t+1* but were not part of the regional patent portfolio in year *t*, and *X* denotes links to technology classes that exit the region between periods *t* and *t+1*.

Aggregate change in technological specialization within a region can then be understood as the sum of five components. The first three components in equation 1 represent changes related to incumbent technology classes within a region, the fourth component capturing

[2] There are a number of different ways to decompose aggregate productivity changes (Griliches and Regev 1995; Caves 1997), but we choose the Foster et al. (1998) version because it measures explicitly the distance of entering and exiting technology classes from the regional cores and because the selection effect can be interpreted in a meaningful way.

the influence of entry into new technology classes within a region and the fifth term representing the impact of a region's exit from technology classes. Of the incumbent terms in equation 1, the first measures the influence of changes in technology relatedness values over time on the aggregate measure of regional technological specialization. If two technology classes move closer together in the EU15 technology space over time, then ceteris paribus, the average relatedness values of regions that contain patents in those two classes will increase. The second incumbent term represents a selection effect. This term is positive (negative) if technology classes with relatedness values higher (lower) than the regional average expand their shares of the region's overall patents. The third incumbent term is a covariance effect that is positive if technology classes characterized by increasing relatedness values over time also expand their shares of the region's patent stock. The entry term in equation 1 is positive (negative) if a region begins patenting in technology classes that are more (less) closely related to its technology portfolio than average. The exit term in equation 1 is negative (positive) if patenting in the region ends within technology classes that are more (less) closely related to the region's technology portfolio than average.

Table 4 depicts the average contributions of each component of equation 1 to changes in regional technological relatedness (specialization) across each of the four periods. Those 5-year periods are indicated by their mid-points. The percentages (in parentheses) are based on the share of each component on the sum of the absolute values of the five components and offer an indication of the relative strength of the factors shaping changes in aggregate regional technological relatedness values. The final row of the table averages the relative contributions of the different components to technological relatedness over the four sub-periods. Although there are differences over time periods and there is considerable heterogeneity in the contributions of components for changes in individual regions, a number of regularities emerge. With the exception of the first period, technological specialization increases on average as the patent portfolios of most regions become more related. The increase in incumbent specialization is driven largely by selection, by increases in regional shares of patents that are located in technology classes that are relatively close to one another. Indeed, over the period as a whole, there is a slight decrease in the overall proximity of patent classes to one another that is captured by the negative sign on the incumbent effect. As expected, exit and selection tend to increase technological relatedness over time, while entry into new patent classes within regions tends to reduce specialization. Although the relative importance of the components changes over time, entry tends to exert the biggest impact on aggregate change, with the exception of the third period when selection is slightly higher. The contribution of entry is highest in the first period, due to rapid growth in the number of technology classes occupied by many regions. Exit tends to be the second most important component in three of the four periods, and selection is the third most important individual component. In most periods, the combined effects of selection and exit result in positive change in technological specialization, overcoming the negative effects of entry.

Table 4: Components of Change in Regional Technological Specialization

Period	Regional change	Incumbent	Selection	Covariance	Entry	Exit
1981-90	-0.00003	-0.00031	-0.00008	0.00092	-0.00247	0.00191
	%	-5.42	-1.42	16.16	-43.44	33.56
1986-95	0.00177	-0.00027	0.00136	0.00076	-0.00191	0.00183
	%	-4.39	22.22	12.46	-31.14	29.79
1991-00	0.00232	-0.00031	0.00235	0.00085	-0.00216	0.00159
	%	-4.29	32.35	11.73	-29.73	21.90
1996-05	0.00103	-0.00047	0.00096	0.00060	-0.00176	0.00169
	%	-8.50	17.53	10.96	-32.11	30.90
1981-05 Average	%	-5.57	18.38	12.83	-34.17	29.04

Note: The values are weighted means for all regions with more than 50 patents. The weights are the number of patents at the beginning of each period. The percentages reflect the share of each component divided by the sum of their absolute values.

While the results of Table 4 are indicative of the drivers of change in technological relatedness as a whole, they obscure considerable heterogeneity between regions. In order to get an idea of the relative importance of the individual components of shifts in regional technological specialization, Figures 4-6 map the relative sizes of the overall incumbent effect (incumbent, selection and covariance variables from Table 4), entry and exit components on technological relatedness over the NUTS2 regions of the EU15. The overall incumbent effect in Figure 4 is dominated by selection and mirrors to some extent the overall changes in technological specialization. The correlation between the selection effect and the change in regional relatedness is 0.61. Regions recording the most marked decline in technological specialization are those with strong negative selection effects. These negative selection effects are particularly strong in the regions of the German Ruhr and northern Italy. A negative selection effect indicates that incumbent technologies close to a region’s knowledge core are declining as a share of the region’s overall knowledge base. This is consistent with a process of technological restructuring in old industrial regions that are shifting resources away from technologies that are perhaps past their prime. Positive selection effects are particularly strong in southern Germany, around London and segments of the UK technology corridor, throughout the core of the Dutch economy, across southern France and parts of Italy. All these regions are expanding invention in technology classes close to their knowledge core.

Figures 5 and 6 report geographical variations in the impact of technological entry and exit on changes over time in technological relatedness. Figure 5 shows that technological diversification has reduced specialization in many regions since 1981. However, in Finland, the influence of entry has been large and positive. This likely represents a dramatic shift of the country into new technological classes that are themselves relatively concentrated in technology space. This is, perhaps, a Nokia effect. Technological entry has also increased specialization in a number of neighboring regions of the former East Germany. Figure 6 shows the influence of exit across EU15 regions. When regions stop patenting in technology classes that are relatively far from their knowledge cores, the average relatedness of technology increases. If regions stop patenting in core technology classes this would reduce

Figure 4: Incumbent Component of Decomposition Analysis, 1981-2005

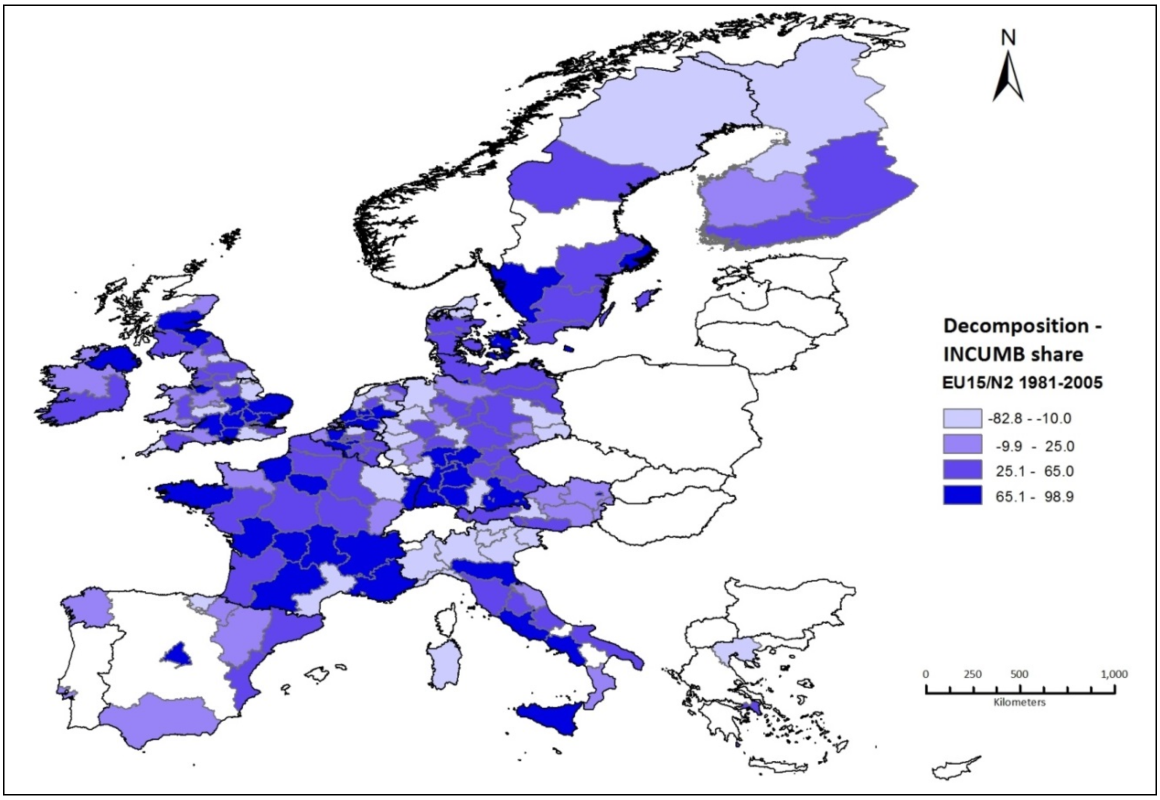


Figure 5: Entry Component of Decomposition Analysis, 1981-2005

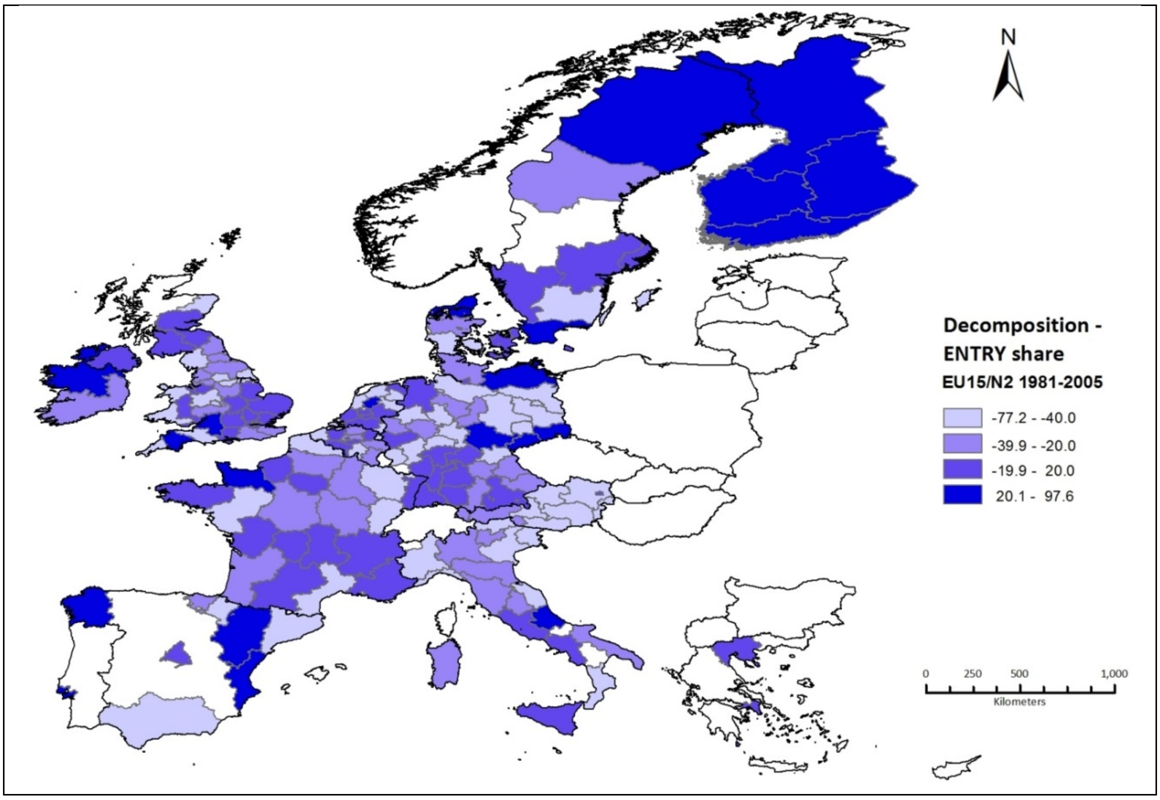
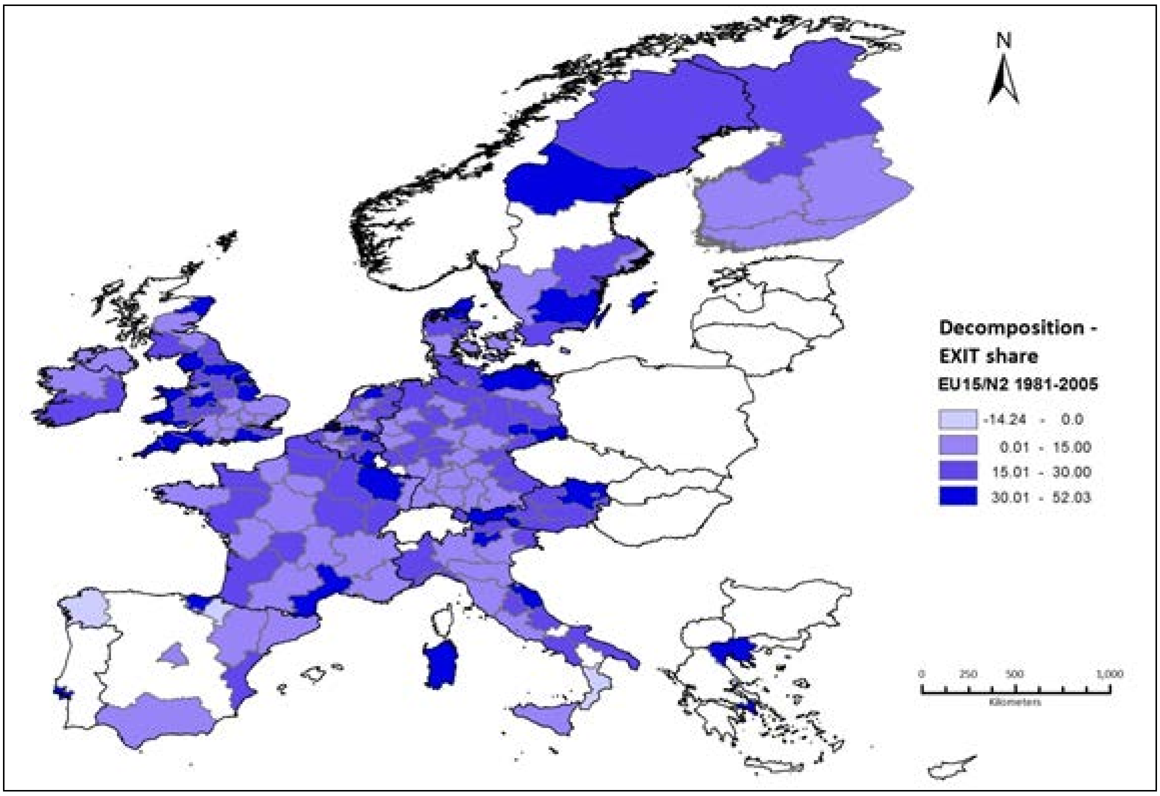


Figure 6: Exit Component of Decomposition Analysis, 1981-2005



technological specialization. Overall, exit increases specialization and the exit effect has been particularly large in several U.K. regions, in Antwerp, Lisbon, Mecklenberg, Dresden and Leipzig, in Nordjylland, Lorraine and Languedoc-Roussillon and Kentriki Makedonia.

We know that changes in the knowledge production practices of regions are shaped not only by processes operating within the region, but also by processes that flow across space. The influence of neighbors on knowledge production practices is left to the next section.

6. Modeling Technological Entry and Exit – the Role of Technological Proximity, Social Proximity and Geographical Proximity

The decomposition of technological specialization across EU15 NUTS2 regions suggests that, at least for some areas, processes of technological diversification (entry) and technological abandonment (exit) play a strong role influencing the concentration or dispersion of knowledge across space. In this section of the paper we explore how existing configurations of technological capabilities within NUTS2 regions shape future trajectories of invention over space. The basic idea is that the technological competence of a region at some time *t*, measured by the region's stock of patents in different technology classes and by the average relatedness between those patents, is likely to influence technological competence in the region at some future time *t+n*. That is, there is some level of persistence or inertia in the technological capacity of a region that guides processes of search and knowledge development and that works to channel effort from older technologies to newer ones.

A simple model assumes that technological diversification builds incrementally upon the existing knowledge base of the region. Thus, diversification to new technology classes, or gaining specialization in such classes, should be a function of their technological distance from the existing structure of knowledge within a region. In Hausmann and Klinger (2007), diversification rests on the density of current practice within a product space and the value of that density around product classes that have yet to be exploited. Boschma et al. (2015) adopt similar claims. We follow a similar logic and hypothesize that the probability of a NUTS2 region diversifying into a technology class is a positive function of the overall proximity (in knowledge space) of that class to all technology nodes in which the region is already specialized (see also Rigby 2013). Along the same lines, it follows that regions will most likely abandon those technologies that are furthest from the core of their knowledge base.

We add to these simple claims measures of the interaction between regions and inventors. Cities and regions do not operate as independent economic units, rather they are connected in more or less dense webs of interaction that link economic agents across different locations. Information flows through these interactions perhaps signaling technological possibilities as yet untried in particular places, as well as the obsolescence of current practice. The greater the flow of information to a region, the more likely it is that the region's knowledge base will be shaped by ideas developed elsewhere. There is some disagreement in the innovation literature regarding the flow of technological knowledge and whether that flow is guided more by spatial or social relationships (Jaffe et al. 1993; Breschi and Lissoni 2005). Thus, we attempt to capture the linkages between regions both in terms of the social and geographical distances between them. While we cannot readily isolate spatial and social relations, for they influence one another in complex ways, our methodology may hint at their relative strength perhaps suggesting pathways for future analysis.

To capture the influence of geographical relationships, we assume that the probability of technological change within a region is influenced by the knowledge bases (structure of knowledge) of other regions. The influence of a region's neighbors is expected to be positively related to their geographical separation. These ideas are operationalized in the following way. First, an inter-regional inverse distance matrix (213x213) is created based on the geographical centroids of each NUTS2 region. The principal diagonal of this matrix contains zeros by convention. Near neighbors in this matrix have higher proximity (inverse distance) values than distant neighbors. Second, for each of the five-year periods examined, a (213x629) matrix of binary location quotients (0/1 values) is constructed that reveals patterns of relative technological advantage (location quotient greater than 1) across the 213 NUTS2 regions and the 629 technological classes of the IPC. A given cell (i, j) in the resulting (213x629) product matrix is the inverse distance weighted sum of the number of region *i*'s neighbors that exhibit relative technological advantage in technology class *j*. Whether or not geographical spillovers of knowledge should exhibit a positive or negative influence on technological diversification and abandonment in a specific region is unclear to us.

In a second measure of inter-regional relationships, we replace the inverse-distance matrix with matrices of co-inventor linkages between all pairs of NUTS2 regions, built separately for each of the 629 IPC technology classes. Thus, we shift from a purely geographical measure of proximity to measures of proximity built around social connections between economic agents in different places. We recognize that the strength of those social ties might still be influenced by geography. To build the square (213x213) matrices of co-inventor relations between all NUTS2 regions for each technology class requires identification of individual inventors. The EPO does not provide such data. Fortunately, Lissoni and colleagues have developed an inventor disambiguation algorithm for EPO data (Lissoni et al. 2006). From these data, we take all patent applications in a given 5-year period and a specific IPC class that list co-inventors and record the NUTS2 regions within which co-inventors are located. We do not exploit the density of co-inventor linkages within the same region in this analysis. Many patents make knowledge claims in several IPC classes. In this case, the co-inventor connections on an individual patent are counted more than once.

The processes of technological diversification and abandonment within EU15 regions are examined using a panel version of a fixed effects logit model. The observational units are the 629 IPC technology classes within each of 213 NUTS2 regions over the five-year time periods that we examine. The values of the dependent variable are 0 or 1, so the regression model is predicting the probability that *Y = 1*, or that a region exhibits relative technological specialization in a particular technology class in a given period. The binary nature of the dependent variable suggests use of a probit or logit model extended to panel form to take advantage of the time dimension in the data. This is not straightforward, for a probit model cannot be run with a fixed effects panel specification that is suggested by a simple Hausman test as preferable to a random effects model. Thus, we make use of the fixed effects panel version of the logit model. We stress that this is an exploratory model of technological diversification and abandonment that we employ to examine whether the broad logic of the claims made above finds some empirical support. We do not offer a richer causal model with additional covariates for that is well beyond our aims.

The model to be estimated is

$$\tilde{Y}_i^{rt} = \alpha + \beta_1 \tilde{T}echProx_i^{rt-1} + \beta_2 \tilde{G}eogProx_i^{rt-1} + \beta_3 \tilde{S}ocialProx_i^{rt-1} + \boldsymbol{\beta} \boldsymbol{\tilde{C}ov_i^{rt-1}} + \boldsymbol{\beta T} + \tilde{\varepsilon}_i^{rt}$$

where the binary dependent variable assumes the value 0 or 1, and represents the probability of region *r* in year *t* exhibiting relative technological specialization in technology class *i*. On the right hand-side of the model, *TechProx* is the time-lagged value of the total distance (in units of technological relatedness) between each technology class *i* and all other technology classes where the city exhibits relative technological specialization. *GeogProx* is a time-lagged and spatially weighted measure of knowledge flows to region *r* from all NUTS2 regions that have relative technological specialization in technology class *i*. SocialProx is a time-lagged measure of the strength of co-inventor linkages between a region and its neighbors within each technology class. **Cov** is a matrix of region and time specific covariates (inventor count) and **T** is a time fixed effect. The final term is an error assumed to possess the usual properties. In equation the ~ indicates that each of the variables have been demeaned with respect to time. This model specification has the major advantage of eliminating omitted variable bias of a form that is fixed over time.

Results from estimating equation with maximum likelihood statistics are displayed in Table 5. Note that the models for entry restrict the observations to those region-technology pairs in which the lagged value of the dependent variable is zero. The models for exit restrict observations to those region-technology pairs in which the lagged value of the dependent variable is 1. The conditional logits drop all region-technology observations for which the value of the dependent variable is fixed over time.

Table 5: Technological Entry and Exit in NUTS2 Regions

	ENTRY		EXIT	
Independent Variables	FE Logit	FE Logit	FE Logit	FE Logit
L. Tech Proximity	2.5180*** (0.0969)	2.3278*** (0.0978)	-1.5073*** (0.1310)	-1.1095*** (0.1340)
L. Geog Proximity		0.0670*** (0.0027)		-0.0990*** (0.0055)
L. Social Proximity		0.0405*** (0.0080)		0.0041 (0.0063)
L. Inventor Count	0.0039 (0.0047)	-0.0031 (0.0046)	-0.0650*** (0.0071)	-0.0647*** (0.0077)
No. observations LL	88449	88449	31360	31360

Notes: FE is fixed effects. * represents significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level. The L prefix shows that the independent variables are lagged one time period. Time fixed effects are included but not shown.

The first column of Table 5 shows that regions are more likely to move into technology classes where they do not yet possess regional comparative advantage (a location quotient greater than 1), when those technology classes are close to the knowledge core of the region. This suggests that the process of technological diversification is dependent on the existing technological competence of the region. As the inventor count in potential new technology classes gets larger, the probability of gaining comparative advantage in those classes does not change. Column 2 of Table 5 suggests that extra-regional linkages play an important role in technological diversification. Diversifying into new IPCs is boosted through building collaborative linkages to inventors in other regions that are active within those same IPCs. Diversification is also assisted through geographic knowledge spillovers. Unfortunately, it is impossible to disentangle which of the independent variables exerts the largest effects in the fixed effects conditional logit model.

Turning to technology exit, column 3 reveals that it is more likely for remote technologies within a region to be abandoned before those technology classes that are close to the knowledge core of the region. Interestingly, a larger pool of inventors in a technology class reduces the probability of technology exit. So while increasing the pool of inventors in technology classes does not encourage entry, it does limit exit. Turning to extra-regional influences in column 4 shows that geographical spillovers of knowledge within the same technology class reduces the probability of exit. Social proximity through region-to-region collaboration within class has no significant impact on technological abandonment.

7. CONCLUSION

We use EPO patent data and co-classification statistics to measure the technological distance between all pairs of IPC knowledge classes. These distances are visualized in a 2-D EU15 knowledge space using Gower's (1971) similarity based multi-dimensional scaling algorithm. The knowledge space reveals the relative proximity (relatedness) of the different patent classes and how the structure of knowledge space has shifted since 1981. The growth of drug and medicine technologies, of information and electronics technologies over the same time period is clear.

Technological relatedness between EU15 patents increased between 1981 and 2005. In other words, the distribution of patents within the EU15 knowledge space has become more compact. This reflects growth in technological relatedness within all aggregate patent technology classes, and even faster growth in the share of patents produced in those aggregate technology classes where individual knowledge subsets are closer to one another than on average. Alongside the growing compactness of the EU15 knowledge space, we show that technological relatedness, or specialization, within individual NUTS2 regions of the EU15 increased on average by 33% between 1981 and 2015.

Changes in technological specialization within EU15 NUTS2 regions were decomposed to examine the influence of technological diversification (entry) and abandonment (exit), along with selection (differential growth within incumbent classes) and an incumbent effect that captures changes in average relatedness between patent classes. Averaged over all time-periods, entry and exit exert the largest influence on shifts in regional technological specialization, responsible for about 34% and 29% of changes, respectively. The exit of regions from technology classes increases specialization, suggesting that technologies remote from the knowledge core of each region are being abandoned. Entry tends to reduce technological specialization within regions, as the process of diversification adds patents to regional knowledge portfolios that are on average further from the core of those portfolios than existing patents. An exploratory regression model links technological entry and exit across the EU15 to the existing knowledge base of regions. The model confirms that patterns of technological diversification and technological abandonment are strongly conditioned by the proximity of technology classes to the knowledge cores of regions. Further, model results suggest that technological choice within regions is also influenced by the knowledge cores of other regions. That influence is mediated both by spatial proximity and social proximity, with the former, perhaps, playing the larger role.

The increase in technological specialization across the EU15 might be taken as additional evidence of the impact of cohesion policy and efforts to better integrate knowledge production sub-systems across the European Union. Further work is required to show whether regional specialization in technological know-how across Europe drives greater returns to knowledge production inputs, and to explore how the institutional structures of regions might be related to the changing technology patterns that we document.

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