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Grasping the complexity of regional knowledge production: Evidence on European regions

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Abstract

Knowledge creation is widely considered as the central driver for innovation, and accordingly, for creating competitive advantage. However, most measurement approaches have so far mainly focused on the quantitative dimension of knowledge creation, neglecting that not all knowledge has the same value (Balland & Rigby, 2017). The notion of knowledge complexity has come into use in this context just recently as an attempt to measure the quality of knowledge in terms of its uniqueness and its replicability. The central underlying assumption is that more complex knowledge is more difficult to be replicated, and therefore provides a higher competitive advantage for firms, or at an aggregated level, regions and countries. The focus of this study is on the conceptual and empirical measurement of knowledge complexity on the regional level of analysis, and on the spatial distribution of complex knowledge created in Europe. We proxy the production of complex knowledge with a regional knowledge complexity index (KCI) that is based on regional patent data. The dataset covers 214 European regions (NUTS-2) from current EU and EFTA member countries. Regionalised patent applications of the most recent five-year period with reliable data (2010-2014) are classified into 35 major technological fields (Schmoch, 2008). The index is comprised – based on the equivalent for economic complexity proposed by Hidalgo and Hausmann (2009) – of two main components: the diversity of a regional patent portfolio, and its ubiquity, jointly defining the degree of complexity of the knowledge produced in a specific region.

The initial results are promising as the regional KCI unveils knowledge creation patterns not observed by conventional measures. Not only that complex knowledge is unevenly distributed in geographical space, the results show that regions specialising in complex knowledge are not necessarily those with the highest overall patenting intensity.

Introduction

Indicators on knowledge production are – by definition – one of the most central concerns in the field of STI studies, considered as a central driver for innovation, and accordingly, competitive advantage of firms, regions or countries (see e.g. Scherngell, 2013, among many others). However, most often the indicators proposed and used capture knowledge production mainly in terms of a pure quantitative perspective, like e.g. number of patents, number of publications and citations, or collaborative R&D projects. By this, it is implicitly assumed that all knowledge has the same value, i.e. the quality of knowledge is often neglected (Balland & Rigby, 2017). This seems a major weakness, since we know very well, for example from the economics of knowledge literature (Foray, 2004), that knowledge or technologies easily to be imitated and diffused in geographical space offer less opportunity for sustainable innovation success. In contrast, the possession of knowledge that is hard to replicate and to move should constitute a major competitive advantage for firms, and respectively regions where such firms are located. Accordingly, rather than counting the number of knowledge inputs and outputs it may be more important to assess the quality of knowledge produced.

In the latter context, the notion of knowledge complexity has come into use quite recently (see e.g. Balland & Rigby, 2017; Sorenson, Rivkin, & Fleming, 2006). The complex nature of knowledge is associated with its value and quality in terms of accessibility and mobility in geographical space, with a higher complexity reflecting increasing quality but decreasing accessibility for others due to its higher degree of 'tacitness'[1] and, accordingly, spatial 'stickiness'. From a complexity science perspective (Fleming & Sorenson, 2001; Kauffman, 1993; Simon, 1962), the complexity of knowledge may be related to the variety of differing knowledge components it contains, and the interdependencies of those components. In relation to this, Kogut and Zander (1993) identify complexity as an important element of what makes knowledge tacit, i.e. the more complex knowledge is, the more it is subject to the individual learning and experiences that can hardly be codified.

This study follows the recent research stream dealing with the conceptual and empirical measurement of knowledge complexity from a spatial perspective, focusing on the regional level of analysis, and the spatial distribution of complex knowledge (Balland & Rigby, 2017). The objective is to apply – for the first time – measures for regional knowledge complexity to a set of European regions in order to characterise the geography of complex knowledge across the European territory. We will define a regional knowledge complexity index (KCI, see the third section for details) that intends to capture the complex nature of a region´s knowledge stock based on patent figures. The KCI relies on the diversity of a region's patent portfolio in terms of the technological fields the patents are applied in, and its ubiquity within a network of technologies recorded in patents. The observed regional KCI is analysed for the most recent five year period with reliable data (2010-2014) for a set of 214 NUTS-2 regions in order to show potential spatial patterns of complex knowledge across the European territory for the first time.

The remainder of this study is organised as follows. The next section discusses the theoretical and conceptual foundations of knowledge complexity, before the subsequent section outlines its formal definition. The fourth section discusses the results of the empirical application of the index to our set of European regions, before the last section closes with some conclusions and a short outlook on a future research agenda.

The concept of knowledge complexity

The notion of knowledge complexity has been highlighted recently in innovation studies when explaining the the spatial distribution of innovative activities (e.g. Balland & Rigby, 2017). In essence, it is argued that traditional studies that try to measure knowledge production lack a consideration of the quality, 'tacitness' and value of knowledge, summarised under the heading of knowledge complexity. The difficulty to conceptualise these dimensions in a rigorous manner, and operationalise them in a robust way is quite obvious, given the – a priori – latent and diffuse nature of knowledge, and even more its value.

In this context, knowledge complexity can be understood as a multi-dimensional measurement concept to capture these dimensions of knowledge (Broekel, 2017). While there have been notable attempts at the firm level (see e.g. Singh, 1997), there are only a few and very recent attempts to conceptualise and define knowledge complexity for countries or regions. These attempts mostly build on the influential work of Hidalgo and Hausman (2009). Their concept of economic complexity grasps the ability of countries to export non-ubiquitous product groups, which can only be traded by relatively few countries. The fact that a country is able to export such sophisticated products competitively should signal the existence of a large set of necessary latent (technological) capabilities which in turn should constitute a competitive advantage. Indeed, economic complexity has been shown to be superior in predicting future economic growth of a country to other indicators such as education and institutional quality (Hausmann et al., 2011). This fundamental concept of economic complexity translates very well to (regional) knowledge production and has recently been applied in the context of knowledge complexity.

In this study, we follow this recent research direction and employ the approach of Hidalgo and Hausman (2009) to capture the complexity of knowledge of spatial entities (countries or regions), using their technological patent portfolio (patents of a specific technological domain applied for in a specific region), and combining – in the same way as done with exports for the economic complexity index – the diversity and ubiquity of the patent portfolio of a country/region in a knowledge complexity index for countries or regions (see e.g. Antonelli, Crespi, Mongeau Ospina, & Scellato, 2017; Balland, Boschma, Crespo, & Rigby, 2018; Balland & Rigby, 2017; Ivanova, Strand, Kushnir, & Leydesdorff, 2017; Whittle, 2017). It is argued that the knowledge complexity index constitutes an advancement of the economic complexity index itself, since the latter is heavily used to draw conclusions on technological capabilities of countries, but neglects an explicit definition of the manufacturing capabilities and their respective knowledge bases (Ivanova et al., 2017). In terms of interpretation, the knowledge complexity index proposed by Balland and Rigby (2017) of countries or regions is understood as their ability to create and sustain knowledge bases that are non-ubiquitous in the system. They show a strong spatial concentration and considerable path dependency in the evolution of complex knowledge among U.S. city regions. Moreover, they find that complex knowledge is indeed spatially more 'sticky' than more ubiquitous knowledge. Other recent papers show a positive impact of knowledge complexity on subsequent knowledge production (Antonelli et al., 2017; Balland et al., 2018) and analyse the conduciveness of the possession of complex knowledge to the later specialisation of a region in a new (complex) technological field (Balland et al., 2018; Whittle, 2017).

The regional knowledge complexity index

Our measure of knowledge complexity also builds on the approach of Hidalgo and Hausmann (2009), though applied at the regional level of analysis. A regions' knowledge complexity is understood as a function of its diversity in terms of different technologies used to produce regional knowledge, and its ubiquity, i.e. how many other regions are capable of producing knowledge related to a specific technological field. Accordingly, the knowledge complexity of regions is based on the region-by-technology network matrix, representing the technological portfolio of all regions as it connects each spatial entity $i = (1 \dots N)$ with the technological fields $k = (1 \dots K)$ in which it is specialised in. Similar to previous literature we use the concept of Revealed Technological Advantage (RTA) by Soete (1987) to find apparent specialisations of regions in technologies for the time period given by *t* (subscript *t* omitted for clarity purposes).

$$RTA_{ik} = \frac{X_{ik}}{\sum_k X_{ik}} \Big/ \frac{\sum_i X_{ik}}{\sum_i \sum_k X_{ik}} \tag{1}$$

The RTA of a region in a specific technological field is the ratio between the share of the regions' knowledge production in this field and the share of the same technological field in the whole sample. The knowledge production, X_{ik} of region *i* in technology *k* is measured by the number of patent applications of inventors located in that region and classified into technological field *k* in period *t*. A value larger than one thus signals a relative regional specialisation in the specific field. Consequently, we define the matrix M as

$$M_{ik} = \begin{cases} 1 \;\; if \;\; RTA_{ik} > 1 \\ 0 \;\; if \;\; RTA_{ik} \leq 1, \end{cases} \tag{2}$$

i.e. elements are set to 1 if a region is specialised in a certain technology, and to zero otherwise. *M* can – from a graph theoretic perspective – also be described as a bipartite graph with two distinct sets of nodes (the *N* regions and *K* technological fields) where only nodes of different types can be connected. Region *i* is connected to field *k* in the European knowledge production network if, and only if, $M_{ik} > 1$. The diversity in knowledge production of region i is then simply given by its degree centrality, $d_i = \sum_k M_{ik}$. Analogously, the ubiquity of k is equal to its degree centrality, $u_k = \sum_i M_{ik}$. Hidalgo and Hausmann (2009) introduced the so-called *Method of Reflections* in order to infer the complexity of countries (and products) from the network of global exports of products. Translated to our notation and applied to knowledge production, this iterative, self-referential algorithm (see equ. 3) takes regional diversification $(d_i = d_i^0)$ and the ubiquity of technological fields $(u_k = u_k^0)$ and then recursively refines these variables with *n* iterations to yield estimates of regional and technological complexity $(d_i^n; u_k^n)$.

$$\begin{cases} d_i^n = \dfrac{1}{d_i^0} \displaystyle\sum_k M_{ik} \, u_k^{(n-1)} \\ u_k^n = \dfrac{1}{u_k^0} \displaystyle\sum_i M_{ik} \, d_i^{(n-1)} \end{cases} \tag{3}$$

In other words, this algorithm produces generalised measures of diversification and ubiquity where each iteration uses information from previous iterations to yield a finer estimate of regional and technological complexity, respectively. Each even iteration of d_i^n is a finer estimate of regional knowledge complexity, calculated as the average ubiquity of technological fields (at iteration $(n-1)$) in which this region is specialised in. Analogously, each uneven iteration of u_k^n produces a better estimate of technological complexity as the average diversification of regions (at iteration $(n-1)$) that are able to produce knowledge in that particular field (for further details see Caldarelli et al., 2012; Hidalgo & Hausmann, 2009; Mariani, Vidmer, Medo, & Zhang, 2015).
It has been shown that it is useful to reformulate the *Method of Reflections* as a fixpoint problem which can be solved analytically without the need of an iterative approach (Caldarelli et al., 2012). Finding the knowledge complexity of regions then corresponds to finding the eigenvector $\widetilde{m}^{[2]}$ associated with the second largest eigenvalue of matrix $\widetilde{M} = \widehat{M}\,\widehat{M}'$, where $\widehat{M}$ and $\widehat{M}'$ are the row-standardisations of M and its transpose. This row-stochastic square matrix $\widetilde{M}$ with regions in both rows and columns shows weighted technological similarities between regions. Elements along the main diagonal can be interpreted as the average rareness of technological fields in which the row and column region has revealed technological advantage. Off-diagonal elements of matrix $\widetilde{M}$ represent the rareness of common technological classes of the row and column region, averaged over all fields the row region is specialised in. We adopt this approach and define the KCI as equivalent to $\widetilde{m}^{[2]}$.[2] A knowledge complexity index of technology classes (TCI) can be obtained by reversing the order of matrix multiplication; $\tilde{T} = \widehat{M}'\widehat{M}$, and analogously solving for the eigenvector $\tilde{t}^{[2]}$ associated with the second largest eigenvalue of matrix $\tilde{T}$.

Empirical analysis

Following related literature, we use patent data to proxy regional knowledge production. Specifically, we retrieve patent applications to the European Patent Office (EPO) by EU and EFTA inventors between 2010 and 2014 (priority year) from the OECD REGPAT[3] database, which offers regionalised patent data. Because the number of patents issued per region varies widely per year, with some regions counting almost no patents, we aggregate patents over a period of five years, as is done in many related studies (see e.g. Antonelli et al., 2017; Broekel, 2017). Due to the slow and path-dependent nature of technological knowledge production, it also makes theoretical sense to sum up patent applications of various years (Antonelli, 2009). Our final dataset covers 214 NUTS-2[4] regions of EU28 plus Iceland, Liechtenstein, Norway and Switzerland (EFTA member countries), where patents were attributed to regions by inventor residence. Patents are classified according to the International Patent Classification (IPC). For our analysis we use the technological classification proposed by Schmoch (2008) which maps IPC classes onto 35 fields. This classification aims to strike a balance between homogeneity in terms of class sizes and technological homogeneity within each technological field and has been used in related literature with comparable datasets (Balland et al., 2018; Whittle, 2017).
Despite the aggregation of five years, many regions barely produce any patents. This is not unexpected considering the inclusion of Eastern and Southern European regions, which historically have recorded very few patents (Fischer, Scherngell, & Jansenberger, 2009). Even though we want to include as many regions as possible, a very small number of patents might adversely affect our empirical results due to biased RTA distributions (Cantwell & Vertova, 2004). Thus, we define a threshold set at 100 patents per region, i.e. we exclude any region that did not produce at least 100 patents in the five-year period analysed,[5] reducing our sample to

292,210.4 patents that are linked to 214 NUTS-2 regions and 35 technological fields. Patents are fractionally counted, i.e. each patent receives a weight of unity along the two dimensions region and technological classification.[6]

Turning to the results, we focus on two main dimensions. *First*, we reflect on the overall ranking of the regional KCI, and *second*, we illustrate spatial patterns of the distribution of complex knowledge in Europe. Table 1 lists the top 15 regions in terms of the regional KCI calculated as defined in the previous section, Table A 1 provides some descriptive statistics on the KCI, TCI and their components.

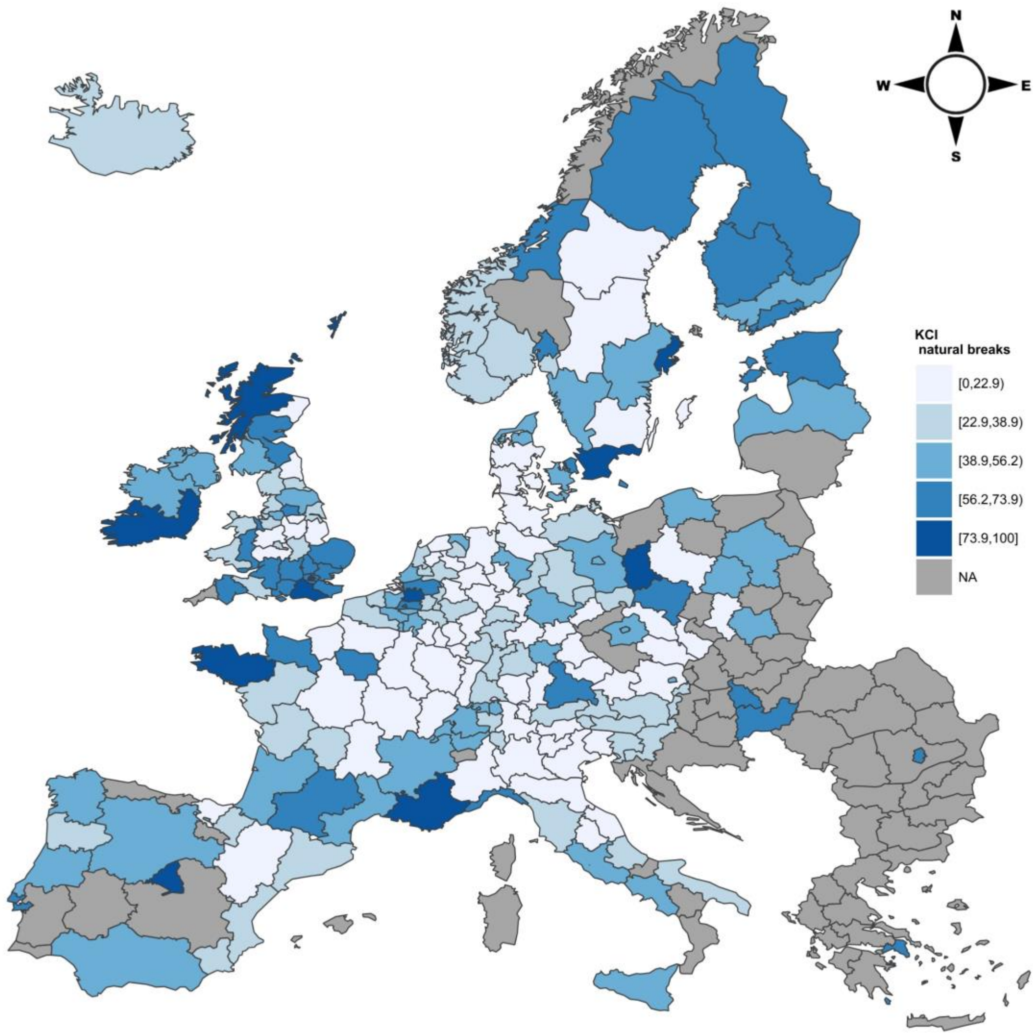
Table 1 Regional ranking of knowledge complexity

NUTS ID	Name	No. of patents	KCI	KCI rank	Div.
FR52	Bretagne	2,296.1	100.0	1	8
UKI3	Inner London - West	1,539.2	91.2	2	9
SE11	Stockholm	4,790.6	90.5	3	9
ES30	Comunidad de Madrid	1,491.6	85.0	4	10
IE02	Southern and Eastern	1,230.3	82.9	5	15
PL43	Lubuskie	128.1	81.9	6	9
UKJ2	Surrey, East and West Sussex	2,095.3	80.8	7	13
UKM6	Highlands and Islands	118.9	80.7	8	7
FR82	Provence-Alpes-Côte d'Azur	2,815.1	79.4	9	11
UKI4	Inner London - East	485.6	78.0	10	13
SE22	Sydsverige	2,800.4	77.5	11	14
BE21	Prov. Antwerpen	1,440.2	73.9	12	12
FR10	Île de France	14,439.7	72.1	13	18
UKM2	Eastern Scotland	747.8	71.3	14	14
NO06	Trøndelag	398.9	71.1	15	14

Note:
Patents are fractionally counted. KCI score is re-scaled to values between 100 and zero.

The initial results are quite interesting, as only Ile-de-France as part of the usual suspects showing the highest overall patenting activity (Ile-de-France, Oberbayern, Stuttgart, etc.) barely makes it into the top of the KCI ranking. Instead, we find a mixture of small and large regions in terms of patent counts within the top 15 regions according to the knowledge complexity index. These regions receive a high complexity score because they are specialised in highly complex technologies (see Table A 2 for the top 15 complex technologies). For example, notwithstanding their relatively low diversification, Bretagne, Inner London – West and Stockholm all specialise in the top 5 most complex technologies (among others) as identified by the network of European patent portfolios. Interestingly, there seems to be negligible relation between regional knowledge complexity and the sheer quantity of patents produced as well as the overall (non-complex) diversification of knowledge production (correlation coefficients: $\rho \approx 0.09; 0.16$, respectively). This possibly indicates that the KCI captures information about regional knowledge bases that is not captured by simply looking at patent activity or overall diversification of a region.

Figure 1 Spatial distribution of regional knowledge complexity



Note: Regions that produced less than the defined threshold of 100 patents are marked as NA.

Shifting attention towards the spatial distribution of complex knowledge in European regions, it seems that there exists a clear spatial pattern where more (least) complex regions in terms of knowledge production are generally situated close to each other. This points to the existence of spatial spillovers, and a certain geographical logic in knowledge creation activities across the European territory. The most prominent example of this is probably an apparent cluster of complex knowledge production in Southern England. What is arguably most surprising is the identification of historically highly actively patenting regions in central Europe (Kogler, Essletzbichler, & Rigby, 2017) as relatively non-complex due to the specialisation of these regions in typical industrial technologies like *Machine tools, Mechanical elements* and others which are deemed non-complex (see Table A 3 for the bottom 15 complex technologies). For example, Stuttgart (ranked 110th in terms of KCI) is historically very active in patenting. However, local inventors are relatively specialised in traditional industrial technologies[7] which are non-complex, according to the TCI.

These preliminary results point to an interesting potential of the KCI in picking up novel patterns in European knowledge production from a complexity perspective. Note, the application of the index will become much more relevant when applied dynamically, i.e. when looking at changes of the KCI ranking and spatial distribution over time. Further, intensive statistical testing is needed to better understand the mechanisms of the index when applied to regional knowledge production, possibly even utilising differing geographical levels and technological breakdowns.

Summary and conclusions

The focus of this study has been on the complex nature of knowledge production analysed at the level of European regions by means of the recently introduced regional knowledge complexity index (KCI). The latter captures regional knowledge endowments in terms of the complexity of technologies in which a region is relatively specialised in. We apply the index – in its most basic form – for the first time for a set of 214 European NUTS regions, using information on regional patenting over the time period 2010-2014. Next to coming up with a regional ranking in terms of their complexity index, we shift attention to a descriptive spatial analysis of the distribution of this index.

The initial results of this descriptive study are promising. *First*, the study demonstrates that the KCI is indeed a highly interesting approach to capture qualitative differences in regional knowledge production. *Second*, the regional ranking reveals that there is no obvious relation between knowledge complexity, quantity of patents produced or (non-complex) diversification of regions. The analysis of the spatial distribution of the KCI reveals a certain geographical logic in knowledge creation activities across the European territory. Surprisingly, traditionally industrial central European regions are often labelled relatively non-complex in terms of knowledge production.

Given these first preliminary results, some interesting ideas for a future research agenda come to mind. *First*, possible dynamic changes of the regional ranking and spatial distribution of complex knowledge production in the European territory could be identified. *Second*, looking at the initial definition of economic complexity by Hidalgo and Hausman (2009), it seems like a promising approach to use patent citations for the KCI – as equivalent to trade exports used in the economic complexity index – capturing more directly the 'knowledge exporting' capabilities of a region. *Third*, alternative and probably more reasonable definitions of technological and regional breakdowns (e.g. accounting in a better way for functional urban areas) are to be considered. *Fourth*, and most importantly, future work will focus on characterising the relationships – by means of dynamic spatial econometric models – between knowledge complexity and regional productivity, assuming that regions with a higher knowledge complexity show higher productivity gains in the long term.

Endnotes

[1] The literature differentiates codified from tacit knowledge (see e.g. Gertler, 2003). The first type corresponds to knowledge that is written down and made explicit, whereas the latter is understood as skills, routines and ideas that are inherent to economic agents and not easily communicated (Polanyi, 1966). The endowment with tacit knowledge forms a central basis for innovation activities and its uneven distribution is a key determinant of the concentration of innovation output in space (Asheim & Gertler, 2005; Maskell & Malmberg, 1999; Pavitt, 2002). Tacit knowledge is spatially sticky because it is by definition not codifiable without difficulty and because it is often very dependent on the social and institutional context in which it was produced (Gertler, 2003; Polanyi, 1966). This relative immobility of tacit knowledge strengthens the competitive position of highly innovative regions (Asheim & Gertler, 2005).

[2] Currently, there is an active ongoing discussion on the best way to extract information about the (economic) complexity of spatial units from the bipartite network that connects these units to products or knowledge subsets that they produce. In the context of economic complexity of nations, Tacchella et al. (2012) introduced a non-linear iterative algorithm that builds on a similar theoretical basis as Hidalgo and Hausmann (2009) but emphasises that the complexity of products should be more strongly limited by the least fit country that is able to export it. This approach termed Fitness-Complexity Method was shown to produce fitness scores that are strongly associated with economic (Cristelli, Tacchella, & Pietronero, 2015; Tacchella et al., 2012) and scientific (Cimini, Gabrielli, & Sylos Labini, 2014) competitiveness of countries. Subsequent studies analysed the mathematical properties (Wu, Shi, Zhang, & Mariani, 2016) and conditions for convergence of this algorithm (Pugliese, Zaccaria, & Pietronero, 2016), which revealed some limitations. The convergence of the algorithm to non-zero values for nodes of the network depends highly on the specific network structure. This is expected to be even more problematic when considering the network of technological portfolios than that of trade (Pugliese et al., 2016). Moreover, the strong limiting factor of the least fit exporting country to the complexity of products can lead to an overemphasis on niche products or technological classes. Hence, knowledge subsets in which only very few regions are specialised in could be identified as complex (and consequently their producing regions), even though they are not inherently difficult to produce but only rare (Morrison et al., 2017). For these reasons we focus on the method described in detail above.

[3] The OECD REGPAT database derives from the European Patent Offce's (EPO) Worldwide Statistical Patent Database (PATSTAT, Autumn 2017); and the OECD patent database. We use the most recent version of the database as of writing this article; OECD REGPAT database, March 2018. Even though data is available until 2017, the period 2010 to 2014 is the most current five-year period with reliable data since patent applications after 2014 have only been added very sparsely to the dataset.

[4] NUTS regions correspond to the NUTS 2013 classification. Patent contributions by inventors located in remote islands or dependencies were removed because of geographic isolation, visualisation reasons and since these regions generally have a very low number of patents. Specifically, NUTS codes ES63, ES64, ES70, FR91, FR92, FR93, FR94, PT20, PT30 were removed.

[5] By doing this, 66 regions were excluded. Note, that patents are often allocated to more than one region and class which means that these patents are not necessarily completely removed from the dataset once a technological field or region to which this patent belongs to is excluded.

[6] Note that many patents fall in several regions and technological fields. Hence, double counting – in contrast to fractional counting - would likely inflate the number of patents considerably, which could lead to very different empirical results.

[7] For example, inventors located in Stuttgart are highly active in non-complex technological fields 27: *Engines, pumps, turbines*, 32: *Transport* and 1: *Electrical machinery, apparatus, energy,* resulting in more than 1,000 patent applications associated with those technologies between 2010 and 2014.

Appendix

Table A 1 Summary statistics

Statistic	N	Min	Mean	Median	Max	SD
KCI	214	0.0	37.7	34.6	100.0	21.7
Diversification	214	5.0	12.6	12.0	19.0	2.9
Number of patents	214	104.1	1,365.5	631.2	14,439.7	1,925.8
TCI	35	0.0	41.5	38.3	100.0	26.6
Ubiquity	35	48.0	76.9	74.0	107.0	16.1
Number of patents	35	529.1	8,348.9	7,229.7	21,269.6	5,134.4

Note:
Mind that the upper part of the table corresponds to regions and the lower to technological fields. Patents are fractionally counted. Complexity scores are re-scaled to values between 100 and zero.

Table A 2 Top technological fields in terms of technological complexity

Field	Description	No. of patents	TCI	TCI rank	Ubiquity
4	Digital communication	13,724.0	100.0	1	48
6	Computer technology	12,168.6	95.3	2	60
3	Telecommunications	5,399.6	92.3	3	61
7	IT methods for management	2,340.7	81.8	4	69
2	Audio-visual technology	5,457.0	77.9	5	58
5	Basic communication processes	1,951.5	69.0	6	54
11	Analysis of biological materials	2,789.2	58.4	7	93
10	Measurement	15,815.8	57.5	8	66
22	Micro-structural and nano-technology	529.1	57.3	9	65
16	Pharmaceuticals	8,878.9	56.2	10	92
12	Control	5,328.9	54.5	11	78
9	Optics	3,994.7	54.0	12	64
15	Biotechnology	7,229.7	52.4	13	101
13	Medical technology	16,686.9	48.2	14	85
8	Semiconductors	4,521.1	47.3	15	53

Note:
Patents are fractionally counted. Technological complexity score is re-scaled to values between 100 and zero.

Table A 3 Bottom technological fields in terms of technological complexity

Field	Description	No. of patents	TCI	TCI rank	Ubiquity
17	Macromolecular chemistry, polymers	5,227.5	28.2	21	64
20	Materials, metallurgy	5,207.4	27.7	22	93
27	Engines, pumps, turbines	13,139.3	26.5	23	60
33	Furniture, games	7,802.8	22.7	24	84
34	Other consumer goods	7,740.3	22.6	25	73
32	Transport	19,557.5	22.1	26	75
1	Electrical machinery, apparatus, energy	21,269.6	20.2	27	69
21	Surface technology, coating	4,122.1	19.2	28	98
35	Civil engineering	14,066.9	19.2	29	107
28	Textile and paper machines	4,516.2	16.8	30	73
30	Thermal processes and apparatus	6,534.5	16.2	31	88
29	Other special machines	12,171.9	8.9	32	102
25	Handling	11,879.7	6.3	33	84
31	Mechanical elements	12,852.5	3.7	34	78
26	Machine tools	8,719.4	0.0	35	63

Note:
Patents are fractionally counted. Technological complexity score is re-scaled to values between 100 and zero.

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