New Indicators of Related Diversification Applied to Smart Specialization in European Regions

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Abstract

This paper proposes two new indicators of related diversification applied to Smart Specialization. The indicators are useful monitoring tools to assess the initial conditions and evolution of the European regions (NUTS 2) regarding one of the orienting principles of Smart Specialization: relatedness. The first indicator ranks regions quantitatively in a given year concerning related variety of specializations; the second one captures to what extent regions acquire, over time, new specializations in related areas. These indexes use the concept of technological relatedness, and are applied to the case of European regions using the OECD REGPAT database. The results indicate that regions located at the core of the European continent, as well as Northern European regions, perform better, whereas Southern and Eastern Europe persistently exhibit lower scores.

Key words: smart specialization, related diversification, patents, European regions

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1. Introduction

The policy concept known as S3 (Smart Specialization) has become increasingly important (Foray, David & Hall, 2011). However, an accepted framework for quantitatively measuring this concept seems to be lacking. According to Foray et al. (2011), S3 is 'a perfect example of "policy running ahead of theory"' (Foray et al., 2011, p. 1) – policy-makers are already developing policy initiatives towards S3, without the tools necessary for measuring it or understanding it in terms of theory. The absence of such a framework constitutes a gap that this article seeks to close, at least in part.

In a recent work, Balland and colleagues propose a framework for the S3. This policy concept concerns developing new specializations (thus the term 'specialization'), in harmony with the local capabilities existing within each region (thus the term 'smart'). Taking this framework of analysis as their point of departure, Balland, Boschma, Crespo & Rigby (2018) associate S3 with the emergence of new specializations, in technologies, industries, or other regional capabilities. Basically, a connection is established between the concept of S3 and the idea of *related variety* at the regional level. Boschma & Gianelle (2014) have also defended a similar idea.

However, the relatedness concept does not appear to have been used for quantitatively ranking regions in terms of their diversification performance in the context of S3. This article utilizes various indicators for capturing the extent to which diversification in European regions is following the principle of relatedness, embedded in the concept of S3. First, an indicator is developed to measure the status of selected regions in terms of diversity, and to what extent the existing pattern of regional variety is in line with the principles of relatedness underlying S3. Then, the article also proposes an index to explain how diversification, according to the principles of S3, has evolved over time for a given set of regions (NUTS 2), also using the concept of relatedness.

Indicators are tested by means of data on patents from the OECD REGPAT database. This yields an analytical framework based on the technological relatedness approach, as the analysis proceeds with the different technologies underlying each type of patents. Compared to other existing relatedness indicators, these indexes are developed to be useful monitoring tools assessing the initial conditions and evolution of the European regions regarding one of the orienting principles of Smart Specialization: relatedness. The methodology adopted here proposes regional vertical prioritization of all technological domains, according to their

potential for regional embeddedness (in the technological structure of the regions). Based on this and on the actual regional technological specializations, the proposed indicators measure, both statically and dynamically, the performance of European regions concerning technological relatedness. Indicators are computed considering the contemporaneous technological structure of the regions, which maximizes the usefulness of the proposed indexes as regional monitoring tools.

This paper has a threefold purpose: to contribute to the literature on S3 by proposing new indicators for measuring the technological dimension of this concept; secondly, to test these indicators, using the OECD REGPAT database; and thirdly, to provide, for the first time, a ranking of European regions in terms of technological relatedness applied to S3, showing how different territories stand and how they have been evolving. Section 2 presents the concept of S3 and the reasons for quantitatively measuring it, as well as why the concept of relatedness is deemed appropriate for this. The datasets are discussed in section 3, while section 4 presents the empirical strategy – methodology and indicators. Main results are presented in section 5. Section 6 discusses few caveats related to the delineation of the data in terms of time-periods, regions, and technologies. Section 7 offers some conclusions.

2. S3 and related diversification

2.1. S3 - The concept of S3

S3 is an approach to innovation policies that aims at prioritizing R&D and innovation projects in those activities where they are more advantageous for a given territory (Foray et al., 2009). This policy is based on 'the simple idea that i) regions cannot do everything in science, technology and innovation and ii) they should promote what should make their knowledge base unique and superior' (Foray et al., 2011, p. 3). With such an approach, this policy necessarily targets the promotion of certain activities, technological fields, and even industries, at the expense of others (vertical prioritization). For this reason, Foray et al. (2011) argue that the S3 approach towards regional development differs radically from common practice otherwise, which is mainly based on horizontal policy measures targeting the overall framework where various economic agents are involved. Also new with this policy concept is the adoption of place-based policies, in contrast to 'one-size-fits all' approaches (Moodysson, Trippl & Zukauskaite, 2015).

Achieving consensus as to how regions should delineate their S3 strategies (and then operationalize vertical prioritization) is difficult. While some have argued that the process should be the outcome of a bottom–up approach (Foray, 2013; Camagni and Capello, 2013; Boschma, 2014), others maintain that, especially in small and non-specialized regions, it should be led top–down (Iacobucci, 2014). In the latter case, regional policy-makers would play a prominent role in the definition of the S3 strategy, whereas in the former it is the stakeholders who delineate the strategy for later adoption by the regional authorities. According to Iacobucci (2014), the bottom–up approach is likely to be biased towards the interests of the involved stakeholders, leading the regions to fail in elaborating an overall regional strategy. McCann and Ortega-Argiles (2015) take a moderate position, arguing that S3 should be approached as a 'partnership-based policy process of discovery and learning on the part of both policy-makers and entrepreneurs' (McCann and Ortega-Argiles, 2015, p. 1300). This perspective is currently the prevalent one (Rodriguez-Pose & Wilkie, 2015; Boschma & Gianelle, 2014; Foray, 2013).

This view is similar to that of Rodrik (2004), who sees the private sector as responsible for identifying new activities, while the role of the government (policy-makers) is to evaluate the potential of the proposed priorities, and then provide the tools for the most capable actors to foster the development of such priority areas. The policy-making authorities may intervene, as long as that does not undermine the market logic underlying the EDP (Entrepreneurial Discovery Process), according to which the entrepreneurs (broadly understood), through trial and error, identify and define priority areas to be developed in the context of the S3 policy. The prominence accorded to stakeholders in this policy framework helps to achieve a decentralized process of prioritization of activities. The adoption of such framework avoids the older top–down policy approaches that deal with prioritization through centralized and bureaucratic procedures.

2.2. S3 as a process of related diversification

Foray (2013) holds that priorities should be defined at an intermediate level of aggregation, somewhere 'between sectors and very micro-activities' (Foray, 2013, p. 59). He also indicates that priority areas should fulfil the principles of inclusiveness (various types of stakeholders should be included), novelty (new sorts of activities should be explored) and relevance (priorities should be pertinent to the regional economy and able to induce structural changes). Thus, emerging new activities should be supported only in the areas that are relevant for those sectors already present in a given territory.

In other words, S3 fosters existing activities in a given region through the emergence of R&D and innovation in new domains that complement existing ones, at least to some extent. This in turn promotes the structural evolution of the targeted economies, through an 'accumulative process that links the present and future strengths of a regional economy in a particular domain of activity and knowledge' (Foray, 2013, p. 63). This process will normally have an inherent logic of related diversification, which can take three forms: transition, modernization or diversification in the strict sense (see examples in Appendix A).[1] Concerning transition and diversification (in the strict sense), if resources are scarce, finite and limited, new activities may replace existing ones (totally or partially), so it may be assumed that there will be competition between the emerging activities and the new ones. With modernization, however, the emerging and existing activities are more adequately characterized by 'complementarity'.

In the context of S3 policy, the term 'specialization' should not be misinterpreted as indicating that such policy targets the specialization of the overall economic structure of a given region. Rather, the underlying idea is to promote the emergence of new areas of activity that build on and complement those already existing, thereby fostering a process of related diversification. In this sense, as Foray (2013) puts it, S3 is 'not about generating technological uniformity and mono-culture or prioritizing sectors or eliminating areas of activities' (Foray, 2013, p. 65). On the one hand, if the priorities are complementary to other activities already present in the region, supporting the former will generally give renewed vigour to the latter, so existing and new activities are not necessarily mutually exclusive. On the other hand, this policy is conceived as being dynamic, so that activities defined as priorities at any given point will not be supported forever, as other priorities are discovered and adopted.

In this sense, technological/industrial relatedness can be seen as a guideline that may be followed by regions as part of their process of S3 (Boschma & Gianelle, 2014). Beyond the fact that relatedness follows the spirit of S3, it appears to have other advantages as well. Relatedness can enhance spillover effects and knowledge transfer, thereby fostering innovation and economic growth at the regional level (see Boschma & Frenken, 2011, for a review). Moreover, related industrial variety is assumed to have a positive effect on the survival rate of companies (Boschma & Wenting, 2007; Klepper, 2007), and a positive/negative impact on the probability of their entering/exiting the market (Neffke & Svensson Henning, 2008). That should not be

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[1] According to Foray (2013), structural transformation can also be unleashed by a process of radical innovation. However, such cases are not dealt with here.

taken to mean that unrelated activities are not viable in a given territory: merely that relatedness can provide an appropriate framework for approaching the topic of S3.

2.3. S3, the need of quantitative tools, and related diversification as an adequate framework

The importance of implementing methodologies to allow the construction of indicators applied to S3 is recurrently mentioned in the literature (David, Foray & Hall, 2009; Barca & McCann, 2011). Moreover, it has been highlighted that empirical studies related to regional S3 are rare, with few attempts as measurement (Iacobucci, 2014; Caragliu & Del Bo, 2013). With that in mind, Caragliu & Del Bo (2013) proposed and estimated a new indicator of S3 based on comparative advantages. However, such indicator of S3 is estimated at a low level of desegregation (only for 15 NACE 2-digit industries), attributing little or no importance to the emergence of new activities or the extent to which they are related to the existing regional structure. What is needed is a framework of analysis, as well as (quantitative) indicators more in line with the principles underlying this policy concept (see, for instance, Foray, 2013).

Several scholars have proposed associating S3 with a process of related diversification (Foray, 2013; McCann & Ortega-Argilés, 2015; Balland et al., 2018). As noted by Boschma & Gianelle (2014), 'the concept of relatedness provides a tool to identify regional (unused) potentials and a framework to target and select promising activities' (i.e. priority areas) (Boschma & Gianelle, 2014, p. 9). Beyond the fact that the related diversification approach is one of the main ideas underlying the S3 policy concept, this approach, as highlighted by Boschma & Gianelle (2014), is well-suited to match the main principles enshrined in the S3 literature, instead of conflicting with most of them. The questionable aspect here concerns the EDP, as the related diversification approaches risk being seen as dealing with prioritization from a centralized perspective. As such, relatedness techniques can be criticized for the absence of entrepreneur intervention in the scope of the vertical prioritization process.

However, Boschma & Gianelle (2014) indicate that these different approaches are not incompatible, and propose a way to reconcile both perspectives. The logic underlying the S3 policy is not inverted unless policy-maker intervention in the process replaces the role that private partners are expected to play: to make the final decision as to the set of areas and activities with greatest potential to benefit from support in terms of R&D and innovation. In this sense, what is suggested is the adoption of a sequential approach, whereby, by means of relatedness techniques, a loose set of areas of activity with higher potential to be supported is

identified. Then, taking these areas as the point of departure, the EDP can be conducted as usual, with the entrepreneurs establishing a vertical prioritization among these pre-selected activities. (Boschma & Gianelle, 2014).

It is under this general framework of analysis that the following sections in this paper should be interpreted. Employing the ideas of S3, relatedness, and priority areas defined according to their degree of relatedness, this article seeks to propose new indicators to approach the topic of S3. Compared to the existing literature, this is the main novelty of this article. It uses the ideas conceptually discussed by Boschma & Gianelle (2014) and the framework of analysis proposed by Balland et al. (2018) about the association of S3 with related diversification, and implements new indicators of variety and diversification to evaluate to what extent such processes, in European regions, are in line with the principle of relatedness. Although the development of relatedness and variety indicators is not new in the literature, the indicators proposed here have never been used before. They were conceived specifically to be as much as possible in line with the principles of S3: development of specializations in those domains that are the most promising (i.e. highest relatedness density) in a given region.

3. Data

This study uses the OECD REGPAT database, which has information on patent applications to the EPO (European Patent Office) as well as the PCT (Patent Co-operation Treaty). To each single patent application, one (or more) technological fields is/are attributed, according to the IPC (International Patent Classification). In this database most patent applications are regionalized, and each patent application (or a share of it) is attributed to each NUTS3/TL3 (or equivalent territorial unit). This enables the use of fractional accounting in assessing the total number of patent applications attributable to a given region.

For each patent application, the dataset includes information on application year: one variable stating the year of actual application to the patent office in question, and another variable identified as 'priority year', defined as the year in which the patent was first filed. Since the aim here is to measure regional technological achievements, the latter concept will be employed, being closer to when the invention underlying a given patent was actually made. This differentiation is relevant because patent application processes involve administrative and bureaucratic procedures, often resulting in time-lags between when the invention was made and

when the application is formally registered at the patent office (Maraut, Dernis, Webb, Spiezia & Guellec, 2008).[2]

Patent applications concerning the EU28 plus EFTA countries (Iceland, Lichtenstein, Norway and Switzerland) were selected. For this group of countries, patent applications were distributed across 44 years, from 1964 to 2015. Overall, for the whole period for these countries, there were 1 722 152 patent application (see Appendix B). However, in some years there were very few patent applications recorded, which might indicate incomplete data. Therefore, such observations were excluded from the analysis: in practice, the period 1964–1979, as well as observations available for 2014 and 2015.[3] Thus, this article uses data from all years within the period 1980–2013. This assures a large temporal coverage, and guarantees that the results are less vulnerable to temporary trends that may affect specific regions during given periods.

For each one of the selected years, and for each region available in the dataset, the number of patent applications pertaining to a given IPC class/subclass is computed. Therefore, for each year and region, this yields the total number of existing patents by IPC class/subclass. As shown in Appendix C, counting the total yearly number of patent applications by IPC class, yields results quite different from the total number of patents. In terms of regional territorial units, although data are available at the NUTS3/TL3 level, it was decided to develop the analysis in terms of NUTS2/TL2, because regional data (from other sources) at NUTS3/TL3 level are generally limited. Moreover, NUTS 2 are the units of analysis that most countries consider to design and implement their S3 strategies. Anyway, the choice of other units of analysis, at either higher or lower level of aggregation than NUTS2, may lead to different results and conclusions than those discussed here (see section 6 for more details).

The use of patent data restricts the scope of this article to the analysis of the technological dimension of S3. The choice of such perspective was mainly driven by data availability. As it is well known, patent data assures a temporal and spatial coverage that is unique (OECD, 2009). Moreover, the fact that patents can be highly disaggregated by different technological categories makes such data particularly suitable for studying processes of regional diversification. Nevertheless, the use of patent data as a measure of inventive and technological activity is not exempt of criticisms, as it presents several limitations. For instance, the

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[2] For further details see Maraut et al. (2008)
[3] As seen in Appendix B, from 2013 onwards there is clearly a break in the series, which is why 2014 and 2015 were excluded from the analysis.

propensity to patent differs substantially across industries (Arundel & Kabla, 1998) and firms, being more difficult to small and new firms to cover patenting costs (OECD, 2009).

4. Methodology

4.1. Step 1 - Revealed Comparative Advantage

The first step is to follow the procedures set out by Hidalgo, Klinger, Barabási and Hausmann (2007) and Montresor and Quatraro (2017), among others, to determine the DoP (degree of proximity) among all technological fields attributed to the patent applications in the dataset. First, for each year and region, the RCA (Revealed Comparative Advantage) is computed for each individual technological field (IPC class or subclass) with at least part of a patent application attributed to it. The RCA is computed according to the following formula:

$$\text{RCA}_{izt} = \frac{PAT_{izt}}{\sum_{z=1}^{n} PAT_{izt}} \Big/ \frac{\sum_{i=1}^{m} PAT_{izt}}{\sum_{i=1}^{m} \sum_{z=1}^{n} PAT_{izt}} \tag{1}$$

where RCA_{izt} represents the Revealed Comparative Advantage of region i, in technology z, at year t, PAT_{izt} is the number of patent applications attributed to technological field z in a given region i and year t, while n and m refer to the total number of technologies and regions, respectively. This indicator, for a given year t and region i, compares the regional share of patents regarding a given technology z, to the share of patents for the same technology as computed for all other regions at time t – thus showing whether a given region, at a given time point, is relatively more or less specialized in a given technology than the rest of the world (all other regions together). If for a given year, region, and technology the indicator has a value greater than one, that means that region i, in year t, has a specialization in technology z.

4.2. Step 2 - Degree of proximity and relatedness among technological fields

Then, for each region and year, all combinations of two technological fields are established for which a given region, in a given year, has at least a share of a patent application. Having this, the DoP between technologies composing a given pair is computed following the formula below, where a and b represent two different technological fields:

$$\Omega_{ab} = \min \{P(RCA_a > 1 \mid RCA_b > 1), P(RCA_b > 1 \mid RCA_a > 1)\}, \tag{2}$$

where P(RCA$_a$> 1 | RCA$_b$> 1)= $\frac{P(RCA_a> 1 \cap RCA_b> 1)}{P(RCA_b > 1)}$ (3)

In (2) Ω_{ab} indicates the DoP between technologies a and b, while the expression P(RCA$_a$> 1 | RCA$_b$> 1) represents the conditional probability of there being, in the sample, cases where technology a has a RCA>1 given that for technology b RCA>1. As regards computing Ω_{ab} and its underlying probabilities, in the sample one observation is a pair composed of a region and a year. Overall, the sample contains more than 8000 pairs of years (1980-2013) and regions. The DoP between two technological fields is computed on the basis of the frequency of finding the co-occurrence of a specialization (RCA>1) in these fields, in the sample of pairs regions-years being analysed.

Although, there are specific techniques to determine technological relatedness, using, for instance, patent citations (Leten et al., 2007) or the co-occurrence of different technologies in the same patent (Breschi et al., 2003; Quatraro, 2010), the article adopts a more general approach based on the concept of RCA (Montresor and Quatraro, 2017). Such approach is followed because RCA methodology can be easily replicated to other sorts of datasets (traded products, employment by NACE 2 sectors, etc.). This feature can allow all that are interested in the topic to extend this analysis (upon data availability), in the future, to other categories of relatedness (beyond technological one). Such exercise would permit exploring other dimensions of S3, and therefore complement the proposed indicators.

'The fact that two technological fields are frequently observed as distinctive advantages across regions may imply that they rely on similar or complementary capabilities and competences' (Montresor and Quatraro, 2017, p.393). However, the criticisms underlying the use of RCA, when mobilized for the measurement of the degree of proximity between technologies, are well known. For instance, Rigby (2015) points out that 'The colocation of patents from different technology classes might be a reasonable proxy for technological relatedness, but might also be a proxy for unspecified economic relationships that display positive spatial autocorrelation' (Rigby, 2015, p. 1926).

In this this article, technologies are proxied by IPC technological classes. This is the most common classification system when EPO patent applications are used. The adoption of 122 IPC classes (technological domains aggregated at 3-digit level) intends to match the level of analysis that is relevant to S3: mid-grained granularity - an intermediate level of aggregation (Foray,

2013). Although in the technological diversification literature higher levels of technological disaggregation may be adopted (Boschma et al. 2015; Rigby, 2015), the choice of IPC classes is according to Balland et al. (2018), who also propose a technological diversification framework for investigating S3 processes in European regions.

4.3. Step 3 - Ranking different technologies according to their average proximity to technological capabilities in different regions

To compute the indicators (see next steps) it is necessary to determine the average DoP between each technology (present or not in a given region) and all other technologies in which a given region has a specialization (RCA>1). That makes it possible to identify, for each region, to what extent the logic of S3 is already embedded there. The ascription of regional embeddedness potential to a given technological area is based on the the average DoP between that area and the technological fields where there are technological specializations for a given region and year. To compute for each one of the technologies their average degree of proximity with the technological specializations found in that region, the following formula is employed:

$$\text{AvgDoP}_{zit} = \frac{f_{zit}}{F_{it}} \tag{4}$$

where $f_{zit} = \sum_{v \neq z} \Omega_{vz}$ (5)

In equation (4), AvgDoP_{zit} is the average degree of proximity of a given technological field z with all other technological specializations v that are present in a given region i and year t; F_{it} is the total number of technological fields v for which there is technological specialization in region i at year t; and finally, f_{zit} is the sum of the DoP between technological specializations v existing in region i at year t and technological field z. This indicator shows the extent to which each technological field z is related to other technological specializations v present within a given region. The index ranges between 0 and 1, where values closer to 0 represent the case in which, for a given year and region, a given technology z is weakly related to the set of technological specializations v present in that region for that year. Conversely, values closer to 1 indicate the contrary.

Having computed the average degree of proximity for all existing technological fields, in all regions and years integrating the dataset, the next step is, using this indicator, to rank technologies. Here it is assumed that the technological field z with the lowest AvgDoP is ranked

1. This means that for a given region and year, the rank of a technology z is 1 plus the number of technologies whose AvgDoP is lower than z.

$$\text{Rank}_{zit} = 1 + \sum_{s \neq z} S_{sit} \tag{6}$$

where $S_{sit} = 1$ if $\text{AvgDoP}_{sit} < \text{AvgDoP}_{zit}$

$$\tag{7}$$

$S_{sit} = 0$ if $\text{AvgDoP}_{sit} > \text{AvgDoP}_{zit}$

where Rank_{zit} represents the ascending rank of technology z in region i and year t in terms of average degree of proximity, while S_{sit} should be interpreted as a dummy variable that takes the value 1 if a technology s in a given region i and year t has a AvgDoP lower than the AvgDoP of technological field z.

4.4. Step 4 - The static indicator: Monitoring initial conditions

To what extent, then, is the logic of S3 already embedded in the regions? To answer this question, this indicator is intended to grasp, at a given point in time, to what extent the situation of European regions in terms of technological variety is in line with the principles underlying S3 (i.e. related diversification). For instance, this may constitute an important tool to understand where European regions stand when S3 policy starts its implementation. While in some regions major efforts may be required, in others this logic may have a long tradition, which is likely to ease the implementation of S3 policy. The indicator is computed as follows:

$$\text{Static}_{it} = \sum_z \frac{\text{Rank}_{zit}\, Spec_{zit}}{MaxRank_{it}} \tag{8}$$

such that:

$$\text{MaxRank}_{it} = \max \text{Rank}_{zit} \tag{9}$$

$\text{Spec}_{zit} = 1$ if $\text{RCA}_{zit} > 1$

$$\tag{10}$$

$\text{Spec}_{zit} = 0$ if $\text{RCA}_{zit} \leq 1$

where Static_{it} represents the degree of variety of region i in year t and to what extent such variety is in line with the principle of technological relatedness; MaxRank_{it} should be interpreted as the

highest rank verified in region i and year t; and $Spec_{zit}$ is a dummy that takes the value 1 if in year t, region i has a specialization in technology z. This indicator shows to what extent a given region has already acquired specializations (RCA>1), attributing higher weight to those whose rank is higher and therefore have stronger potential for regional embeddedness. Each component of the sum belongs to]0, 1], such that regional technological specializations that reveal the lowest proximity to the existing regional technological capabilities are very close to zero. Reversely, if the region is specialized in technologies that present the highest rank, they contribute to the sum as one. At bottom line, specializations that are more distant to the existing regional technological capabilities provide a modest contribution to the indicator. Oppositely, specializations that are closer to the existing regional technological endowments provide the most relevant input to (8).[4]

Finally, as the upper and lower limits of (8) vary from period to period, and as one of the objectives of this article is to carry out comparisons across different periods, in each year t (8) is rescaled to go from 0 to 1. The conversion is implemented as follows:

$$\text{Rescaled Static}_{it} = \frac{\text{Static}_{it} - \text{MinStatic}_{it}}{Max\text{Static}_{it} - \text{MinStatic}_{it}} \qquad (11)$$

4.5. Step 5 - The dynamic indicator: Monitoring evolution

The second indicator is a dynamic monitoring tool, since it is designed for measuring to what extent European regions, during a given time period, acquire new specializations and to what extent such areas are closely related to previous regional specializations. The evolution of a given region is here defined in terms of its acquisition of new specializations during a five-year timespan (Balland et al, 2018; Cortinovis et al., 2017, Xiao et al., 2016). As previously, this indicator also attributes a higher weight to new specializations that are closer to pre-existing technological specialization structure of the region:

$$\text{Dynamic}_{it,t+5} = \sum_z \frac{\text{Rank}_{zit}\, New Spec_{zit+5}}{Max Rank_{it}}$$

(12)

such that:

[4] As a robustness check, the indicator has been recomputed, but now assuming Fit as the total number of technological fields for which there is at least a share of a patent attributed to the region i at year t, while fzit should be now interpreted as the sum of the DoP between technological fields existing in region i at year t and technological field z. As the two version of the indicator do not yield substantially different results, the paper uses only the first version of the index.

$$\text{NewSpec}_{zit+5} = 1 \text{ if } \text{RCA}_{zit+5} > 1 \wedge \text{RCA}_{zit} \leq 1$$

(13)

$$\text{NewSpec}_{zit+5} = 0 \text{ if } (\text{RCA}_{izt} > 1 \wedge \text{RCA}_{izt+5} > 1) \vee \text{RCA}_{izt+5} \leq 1$$

and $z \in \text{NonSpec}_{it}$ (14)

where NonSpec_{it} is the set of technologies that in a given year and region satisfy the following condition:

$$\text{RCA}_{zit} \leq 1$$ (15)

where $\text{Dynamic}_{it,t+5}$ is an index measuring the evolution of region i, between year t and t+5, in terms of the acquisition of new specializations, and NewSpec_{zit+5} is a dummy that takes the value 1 if, as of year t, the region i did not have a specialization in z, but acquired it five years later. MaxRank_{it} and Rank_{zit} are defined as previously, with the difference that now only technologies in which regions are not specialized in are ranked (see conditions (14) and (15)). As previously, the index is rescaled to range between 0 and 1.[5]

5. Results

The empirical analysis starts by observing the static indicator (8) that measures the degree of technological variety exhibited by a given region, and the extent to which such variety includes technologies that are the most related to existing regional technological capabilities, for each year. Table 1 presents the descriptive statistics for this indicator for those years for which it is computed. The number of observations per year increases over time – the sample includes 225 regions in 1990, 258 in 2000, and 275 in 2013 – because some regions have reported patent data only for recent years. Concerning the results obtained for the rescaled index (11), the average value ranges between 0.39 (in 1990) and 0.43 (in 2013). On the one hand, this means that, on average, the analysed regions are below the centre of the scale (i.e. 0.5). On the other hand, their average performance has slightly improved over time. In 2013, the maximum value observed for the rescaled static indicator was found in the region of Veneto (northeastern Italy).

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[5] Two versions of this indicator are computed: one, referred to as 'standard', where NonSpec is simply considered as the set of fields without a specialization at time t (RCA≤1), and another, 'restrictive', where NonSpec includes only technologies with RCA<0.5 at time t. The paper uses only the standard version of the index, whereas the two versions (standard and restrictive) do not yield substantially different results.

In that year, the region with the lowest score was Stredne Slovensko (Slovakia). This means that in 2013, this region had few specializations in those technologies in which it had the highest potential for regional embeddedness. The maximum value of related variety in absolute terms (38.14) was recorded in 2000, for Arnsberg (Germany). In 2000, the region with the lowest scores also registered 0 for the indicator in question: Severozapaden (Bulgaria). Finally, in 1990, the highest value was verified again in Arnsberg (Germany). The lowest level corresponds to Cantabria.

< Table 1 about here >

Observing the left-hand side of figure 1, there are two main conclusions to be drawn. First, between 1990 and 2013, most of the regions show a positive evolution in the static index, indicating improvements over time in the acquisition of specializations in technologies with the highest regional embeddedness potential (despite a few exceptions). This is especially visible for some less developed regions. For instance, in 2013, figure 1 shows that some peripheral regions present high scores. Second, almost all regions that occupy leading positions are located at the core of the European continent or in the north, whereas lower scores are found in regions in eastern and southern Europe (mainly Portugal, Southern Italy and Greece). This fact suggests that, probably, data are not randomly distributed across space. This hypothesis is confirmed by the Global Moran's I statistic (0.47 in 1990, 0.54 in 2000 and 0.42 in 2013)[6], which indicates that, globally, the value of the static indicator in a given region is more similar to its immediate neighbours than it would be the case randomly (see right-hand side of figure 1). As the right-hand side of figure 1 shows, this global statistic is driven by the Local Moran's I statics of those regions in the 1st quadrant (regions in leading positions surrounded by leading neighbours) and 3rd quadrant (regions in bottom positions surrounded by low performing neighbours), while remaining observations contradict this trend.

< Figure 1 about here >

Appendix D shows that Austria has the highest median value for the static indicator in 2013 (0.62). The lowest median values in 2013 are for Bulgaria, Greece and Romania. In 2000, the highest median value was recorded in Lichtenstein, followed by Austria, Germany, Sweden, Finland, Denmark, Luxembourg and France, all with a median above 0.5. Among the countries

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[6] Moran's I statistics are computed based on regional (queen) contiguity. Thus, non-neighbors (regions that do not share the same border) are assigned 0 in the spatial weights matrix. For the sake of simplicity, Islands are excluded from the computation of Moran's I statistics.

with lower median values, are the Bulgaria, Czech Republic, Estonia, Greece, Hungary, Lithuania, Malta, Poland, Portugal, Romania and Slovakia, all with median scores lower than 0.2. Also in 1990, the countries with the highest figures for median value of the static indicator are Switzerland (0.71), Lichtenstein (0.68), Sweden (0.62), Germany (0.57), Finland (0.56), and France (0.55). Bulgaria, Croatia, Greece, Hungary, Iceland, Poland, Portugal, Romania, and Slovakia were the lowest. Appendix E corroborates this impression of a dichotomy between northern / central European regions on the one hand, and southern and eastern European regions on the other. In 2013, most countries where less than half of the regions exhibited a score of the static indicator below the median were mainly in southern and eastern Europe, whereas those where more than half of the regions were above-median score were mainly northern and central European countries. There are some exceptions, however.

To what extent, then, is there a correlation between the static indicator, and some regional macroeconomic variables – GDP per capita in particular? Analogously, is there a correlation between the proposed index and other regional indexes (Regional Competitiveness Index, Regional Innovation Index, and the Regional Quality of Institutions Index)? [7] Moreover, given the way the indicator (8) was constructed (using data on patents), it is also important assess the correlation between the index and the number of patents within each region (the absolute numbers and per capita values). A high degree of positive correlation between patents and the proposed index might mean that the indicator could be biased, as it attributes (by construction) higher scores to regions with higher absolute/relative numbers of patents. However, as shown in Table 2, this is not the case: the existing correlation between the proposed indicator and patents (total number and per capita values by region), although positive, is very low. Concerning GDP per capita, as expected, there is a moderate and positive correlation between this variable and the indicator. Although stronger, the correlation between the proposed indicator and each of regional indexes mentioned above is also positive and moderate. In other words, the fact that northern and core central European regions perform better in the achievement of technological specializations with higher regional embeddedness potential, is not simply explained by the fact that these regions have typically a higher level of economic and technological development. It seems to be more related to their competitive, innovative and quality of institutions performance. Anyway, again, these elements do not explain all. Probably,

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[7] Data on these indexes are collected from Annoni & Dijkstra (2013)

patterns of specialization in top priority areas are also related to policy strategies and choices made by the regional and national authorities.

< Table 2 about here >

Table 3 presents descriptive statistics on the computation of indicator (12), which reflects to what extent regions, between year 2008 and 2013, acquired new specializations, and the extent to which such new specializations are those most related to the existing regional technological capabilities.[8] The indicator was computed for 269 regions and its average is equivalent to 0.44. This means that, on average, in 2013, the performance of the analysed regions is slightly below the centre of the scale. The highest score goes to Autonomous Province of Trento (northern Italy); the regions with the lowest scores are Sud-Est (in Romania), Notio Aigaio (Greece), Algarve and Alentejo (both in Portugal), and Corse (France).

< Table 3 about here >

The geographical distribution of regions' scores on this indicator (see figure 2) shows that regions with the highest scores are somewhat more widely spread across the continent than in the static indicator (see figure 1). High scores for the core of Europe are less predominant, compared to the static indicator; and some southern (e.g. Spain) and eastern European regions exhibit very high scores, although some central European regions have quite low scores. This means that some peripheral European regions have been evolving towards acquiring new technological specializations in domains that are closely related to those that existed previously in the regions. To some extent, this trend confirms that S3 may be a feasible strategy for non-core peripheral areas, mainly in Southern and Eastern Europe, despite the huge challenges these regions still face (McCann & Ortega-Argiles, 2016). Although the results discussed here cannot be attributed to S3, they confirm that even some of the regions located in geographical areas that typically exhibit lower scores in terms of related diversification, are able to engage in the spirit of S3. This reinforces the idea that S3 applies to every region, regardless its level of economic development.

< Figure 2 about here >

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[8] As a robustness check, the indicator was also computed for the periods 2009-2013 and 2010-2013. However, the change of the time window does not yield substantially different results.

One potential limitation of this index is the fact that at time t, the number of technological specializations differ from region to region. This implies that the number of technologies in which each region is potentially able to create new specializations, between t and t+5, also differs substantially. As the indicator proposed in (12) is additive, it is possible to think that it might be biased towards regions with more opportunities of new specializations, overestimating their diversification performance. To investigate this, Table 4 shows the correlation between the indicator and the number of technologies in which each region is potentially able to create new specializations, between t and t+5. However, the correlation between both variables is negative (see Table 4). This means that there is a negative association between more unexplored specializations, and the regional performance in terms of the dynamic indicator.

< Table 4 about here >

Another potential limitation is that as in (12) MaxRank differs from one region to another, it would be possible to argue that regions where MaxRank is higher, the contribution of each element of the sum (each technology in which regions acquire new specializations) might be of lower magnitude, justifying therefore the negative correlation discussed above. However, the average strength of each technology (see table 5) is almost the same in all regions, regardless their number of unexplored specializations. Briefly, this means that what matters is in how many and what technologies regions create new specializations, and not the number of technologies that the region has available to do so.

< Table 5 about here >

Finally, applying the static indicator for 2000 and 2013, a cluster analysis exercise[9] is performed. For each of these years, the sample of regions is split into two non-overlapping groups corresponding to those with the highest (leaders) and lowest (followers) scores. Depending on the category attributed to each region in both periods, territories are then categorized as Technological S3 persistent leaders (leaders in both years), Technological S3 recent leaders (followers in 2000, leaders in 2013), Technological S3 persistent followers (followers in both years), and Technological S3 recent followers (leaders in 2000, followers in 2013). Further, the static index is used in its rescaled version (see equation 11). The cluster analysis yields 0.43 as the threshold for the static indicator in 2000. Regions with a score below this threshold are seen

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[9] *k means*

as *Technological S3 followers;* those with a score above are seen as *Technological S3 leaders.* For 2013 the threshold is fixed at 0.38.

Figure 3 shows the representation of the regions, and their classifications, according to the established thresholds resulting from the cluster analysis described above. Appendix F presents in detail the values attributed to the regions, and their standing in terms of the four categories. The upper right-hand portion of the graph (persistent leaders) shows the dominance of German regions, along with some Italian, Finnish and Austrian territories, among others. In the bottom left-hand portion (persistent followers) are several regions belonging to southern and eastern European countries, notably Bulgaria, the Czech Republic, Greece, Hungary, Poland, Portugal, Romania, and Slovakia (see Appendix G). However, in the 'persistent followers' category there are also some Austrian, German, Finnish, French, British, Swedish and Dutch regions. Thus, regional heterogeneity in terms of the ability of the regions to diversify into those technologies with higher regional embeddedness potential is found not only among regions of different countries, but within countries as well.

As to recent leaders, Figure 3 highlights, for instance, Galicia (ES11) as showing a noteworthy development between 2000 and 2013. This region evolved from a score equivalent to 0.18 in 2000, to more than 0.61 in 2013. Interestingly, the top left-hand portion of the chart (recent followers) has few regions, which would indicate that regions once considered to be Technological S3 leaders rarely worsen their standing substantially later on – as with Upper Palatinate (DE23) and Continental Croatia (HR04).

< Figure 3 about here >

6. Discussion of the indicators and the delineation of the data: time, space and technologies

This paper provides indicators specifically applied to S3. The gradual construction of these indicators (step by step) allows the easy replication of the proposed indexes, using other datasets, units of analysis (other than NUTS 2) and time-periods. Moreover, this can be done even for other purposes, beyond S3. Although the results of the indicators are always contingent on the data and methods adopted, the article has proposed several robustness checks to confirm that its main conclusions do not change substantially when there are variations in few of the adopted methodological decisions. Nevertheless, there are aspects related to the delineation of the data that require a more careful discussion, especially in case the indicators are used in other contexts.

The first caveat is the time-period selected to compute regional technological specializations. Once a new patent is invented, it can be exploited for several years. Thus, it might make sense to think that the computation of technological specializations of a given region, in a given year, should not consider, exclusively, patent applications of that year. Thus, an alternative approach would have been computing regional technological specializations based on the overall stock of patent applications that exist in a given region. However, such method has few drawbacks. Computing regional technological specializations based on current and past patent applications would imply considering patent applications that are too distant in time. The risk is that the technologies that such patents represent are both obsolete and no longer relevant for the region. To avoid including irrelevant patent applications in the computation of the regional technological specializations, it would be necessary defining a time threshold. Such threshold would determine which previous years' patent applications would be relevant, and which ones would be irrelevant. However, this decision would always be random.

Moreover, computing technological specializations of the regions based on a single year patent applications' data, only means that a new trend is emerging and the region is diversifying following such trend, which is exactly what this paper seeks to investigate. Therefore, the fact that a given region is not considered specialized in a given technology based on yearly data (and it might be considered specialized when several years' patent applications are considered), simply means this technology does not belong to the new wave of technological specializations that is emerging, while others belong. This approach captures better the evolutionary nature of S3 processes, than an alternative approach where too distant and obsolete technologies are also considered. Moreover, as such approach allows a contemporaneous assessment of the evolutionary path regions are following, it will be more useful for policy makers as a monitoring tool.

The second important caveat is the delineation of the data across space (i.e. the territorial units adopted for the analysis). The paper selects NUTS 2 as units of analysis because, beyond the fact they are the functional regions that most countries consider to design and implement their S3 strategies, Eurostat also regards NUTS2 as the relevant territorial units for the application of regional policies. However, it can be the case that that these are not functional regions for more specific diagnoses, such as to analyze how different industries or technologies are clustered across the space. It can be the case that different regions when analyzed together are specialized in given technologies, while individually they are not. Reversely, sub regions within each NUTS2 may also be considered specialized in specific technologies, while the overall

NUTS2 are not. These aspects may be particularly relevant if the proposed indicators are mobilized to perform more micro-level analyses, such as investigating the dispersion of specific sectors or technologies across the space.

If so, one important issue may be to understand what the relevant spatial units are, to study the clustering of similar or related technologies. This may differ from country to country, and even within countries, depending on the technologies, industries or sectors at stake. The aggregation of the data into specific spatial units, according to the objective of the research, may have implications, for instance, in the analysis of distance decay effects. The intensity of spatial interactions between territories (and between their technological sectors) will depend on how regions are operationalized. This will influence both the distance assumed to exist between territories, as well as their intensity in different technologies and activities. For all these reasons, delineation of the data across the space requires caution, as it should match the specific objectives of the research.

The third and last caveat concerns technologies, namely their categorization system and the methods adopted to compute technological relatedness. The adoption of technologies according to the IPC categorization system, and their operationalization using three digits, is also contingent on the objective of the research. As discussed above, this choice is mainly driven by the objective this article: provision of indicators applied to S3. However, if the indicators are used for other purposes, it may make sense to operationalize technologies in alternative ways. This would be the case, for instance, if the research were focused on a specific set of technologies (e.g. green technologies, nanotechnologies, ICT related technologies). In such case, it may be necessary an alternative (and more detailed) operationalization of technological categories.

As previously discussed in section 4.2, the degree of proximity between technologies is the outcome of the co-occurrence in the space of technological specializations. This may be regarded as an ex-post measure of relatedness inspired, for instance, in Hidalgo et al. (2007). This slant contrasts with ex-ante approaches to relatedness, according to which proximity is determined a priori, regardless any empirical pattern demonstrated by the data (e.g. co-occurrence in the space of technological specializations, patent citations, the co-occurrence of different technologies in the same patent, etc.). This ex-ante perspective is adopted in the widely used entropy measures of relatedness. One well know example is Frenken et al. (2007) who, to evaluate the degree of related variety in employment in Dutch regions, measure the variety of

employment in five digit sectors (of economic activity), within two digits sectors (of economic activity). The implicit assumption is that all sectors that share the same 2 digits are related, as they belong to the same parent group, according to a pre-defined taxonomy.

Following this method, technological relatedness would be based on a pre-existing hierarchical categorization of technologies (for instance, the IPC classification system). However, relatedness would be very dependent on the categorization system adopted. Moreover, such approach would not allow the vertical prioritization of technologies according to their degree of proximity to the existing regional technological structure (see section 4.3). It would only determine whether technologies are related or unrelated. However, it would be impossible a strict prioritization of technological domains according to their potential for embeddedness in the regional technological structure. Oppositely, ex-post approaches seem much more adequate. They allow the computation of a continuous variable that evaluates the degree of proximity between different pairs of technologies, enabling strict prioritization of technologies.

Although this is the approach adopted in this paper, it also implies few limitations. For instance, section 4.3 ranks technologies according to their degree of proximity to the existing regional technological structure. However, the use of the ranks to construct the indicators (see sections 4..4 and 4.5) determines, implicitly, the adoption of an ad-hoc weighting of the different technological domains. As such, another weighting scheme may have resulted in a different outcome than the one obtained. In spite of this limitation, this choice allows prioritization, which is an important aspect to S3. Nevertheless, the use of the proposed indicators to investigate alternative research topics may require adjustments.

7. Conclusions

The concept of S3 has been growing in importance, becoming a regional innovation policy concept aimed at fostering R&D and innovation investments in activities deemed to have greater potential for regional economic development. Operationalization of this concept requires vertical prioritization, which should be done through an EDP, as described earlier.

What has been lacking is an analytical framework for dealing quantitatively with S3, while respecting its main principles. This article has proposed employing the concept of *related technological diversity* in order to frame this policy concept. Under such framework, two indicators are proposed: one that measures, at a given point in time, to what extent a given region has specializations in those technologies with highest relatedness density, and one that

evaluates, over time, to what extent regions acquire new specializations in related areas. These indicators are conceived being as much as possible in harmony with the main principles set out in the literature on S3 policy.

Testing these indexes by means of data on patents has indicated that the process of related technological diversity is more developed in regions in the core and the north of the European continent. In contrast, regions in southern and eastern Europe persistently exhibit lower scores. As regards development between 2008 and 2013, the highest and lowest scores are scattered across Europe, but with a concentration of below-average scores in eastern Europe. This aggregation of very high and very low results in certain geographical areas may indicate spillover effects associated with this policy concept. Despite the dichotomy between the northern and central regions, and the southern and eastern regions, the analysis reveals noteworthy dissimilarities across regions within the same country. On the one hand, especially in the most recent years, relatedness is becoming more and more dispersed. There are top performing regions in terms of relatedness that are located in peripheral and economically disadvantaged areas of Europe. On the other hand, within countries heterogeneity may indicate that S3 and its inherent logic of related diversification should be seen as not depending solely on national policies: also region-specific factors need to be taken into consideration. All this supports S3 as a policy potentially adequate for all European regions, including non-core and less developed ones. Nevertheless, the persistence of some low performing regions highlights some deeply rooted problems that policy makers should carefully consider to make S3 a successful policy initiative for every European regions.

Division of the sample into different groups of regions according to their relative degree of technological related variety in 2000 and 2013 indicates that most of the territories examined can be categorized as either technological S3 persistent leaders or technological S3 persistent followers: substantial changes in the relative position of the regions are fairly rare. It is even rarer to find regions that qualify as technological S3 recent followers (regions whose relative position fell substantially between 2000 and 2013). This may indicate that, having engaged in a strong pattern of related technological variety, a region will tend to follow persistently such standard.

Although the idea of S3 should be applicable to any region, the indicators, computed using patent data, can be estimated only for regions and years with patents in more than one technology. Further research should focus on developing more inclusive indicators applied to

the concept of S3. As highlighted by McCann & Ortega-Argiles (2016), 'the benefits of RIS3 tend to be multi-dimensional rather than purely technological and research-related, also involving institutional and governance dimensions'(McCann & Ortega-Argiles, 2016, p.1422-1423). Anyway, the proposed indexes should be regarded as a complementary tool to others available (see, for instance, the S3 Platform). Another strand for future research concerns the determinants of the ability of regions to follow a S3 pattern. The results indicate that GDP per capita and the institutional framework existing within each specific region should be seriously considered as elements with some explanatory power over the capacity of the regions to diversify into the most related technologies. However, further investigation is needed here.

Finally, this study, based on the technological topography of selected regions, has sought to enable some conclusions on their situation in terms of related diversification. The objective of this exercise has been to explore the technological dimension of the concept of S3, creating indicators able to embed some principles of technology-related diversification that are inherent to the logic S3. Future research should investigate to what extent the regional S3 strategies of different territories are in line with the technology-related diversification logic applied in this study.

Acknowledgements

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Table 1. Static indicator, by year

	Indicator			Rescaled Indicator		
	1990	2000	2013	1990	2000	2013
N	225	258	275	225	258	275
mean	14.69	16.11	15.32	0.39	0.42	0.43
max	36.67	38.14	34.61	1.00	1.00	1.00
min	0.49	0.00	0.52	0.00	0.00	0.00
std dev	8.56	8.74	7.32	0.24	0.23	0.21

Source: author's computations

Figure 1. Rescaled Static Indicator (1990, 2000, and 2013) - Geographical distribution (left-hand side) and Moran's I statistic (right-hand side)
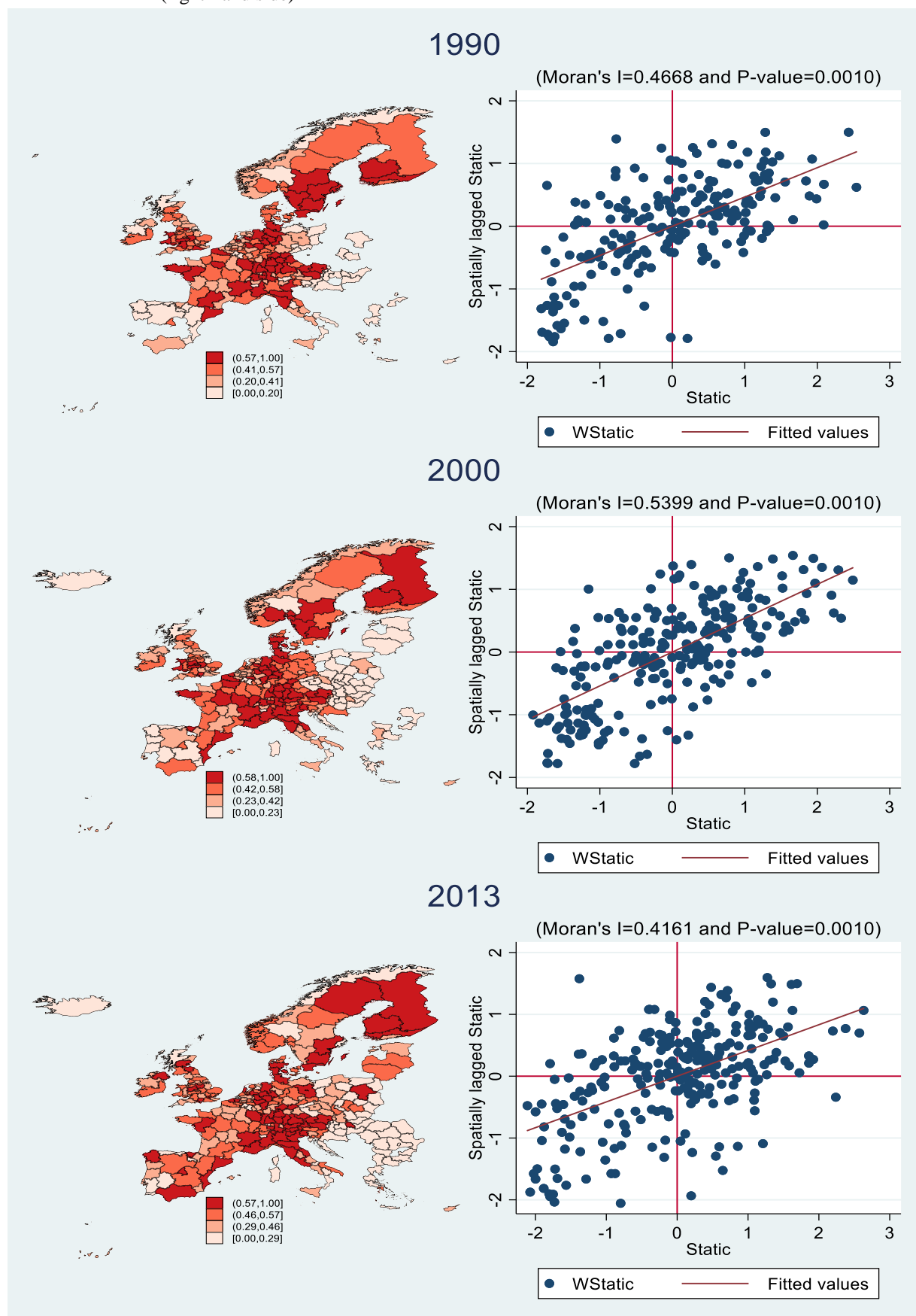
Source: author's computations

Table 2. Correlation between different sets of variables (2013, 2000, and 1990)[10]

	Patents	Patents pc	GDP pc (PPP)	Competitiveness	Innovation	Institutions
N	758	677	478	235	235	235
Rescaled Static Indicator	0.22***	0.13***	0.45***	0.58***	0.57***	0.51***

***Correlation significant at the 0.01 level; **Correlation significant at the 0.05 level;

*Correlation significant at the 0.1 level

Source: OECD (2016), Eurostat, Annoni & Dijkstra (2013), and author's computations

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[10] For GDP pc there are no data for 1990, which explains the lower number of observations when compared to patents. In the case of Regional competitiveness, innovation and quality of institutions indexes the data concern exclusively 2013.

Table 3. Dynamic indicator (2008-2013)

	Indicator	Rescaled Indicator
N	269	269
mean	8.29	0.44
max	18.58	1.00
min	0.33	0
std dev	3.55	0.19

Source: author's computations

Figure 2. Rescaled Dynamic Indicator (2008-2013)
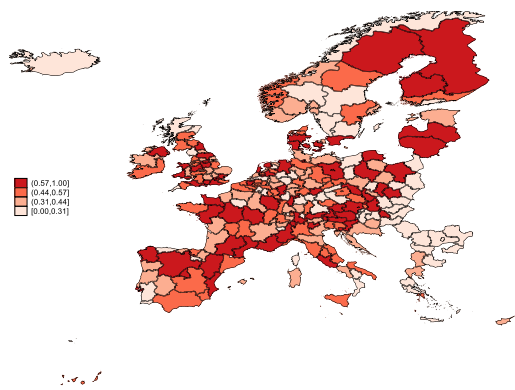
Source: author's computations

Table 4. Correlation between the Rescaled Dynamic Indicator and the number of technologies with no specialization in 2008.

	N technologies with no specialization in 2008
N	269
Rescaled Dynamic Indicator	-0.45***

***Correlation significant at the 0.01 level; **Correlation significant at the 0.05 level; *Correlation significant at the 0.1 level

Source: author's computations

Table 5. Average strength of each technology with no specialization in 2008

	N technologies with no specialization in 2008 (2)	Sum of the strength of all technologies with no specialization in 2008 (1)	Average strength of each technology with no specialization in 2008 (1/2)
N	269	269	269
mean	97.17	49.08	0.51
max	120	61	0.51
min	63	32	0.50
std dev	12.62	6.31	0.00

$(1) = \sum_z \frac{Rankz_{it}\ NewSpec_{zit+5}}{MaxRank_{it}}$ as defined in equation (12)

(2) = MaxRank$_{it}$ as defined in equation (9)

Source: author's computations

Figure 3. Distribution of European regions according to degree of diversity and relatedness in technological areas, 2000 and 2013

Source: author's computations

Appendix A - Examples of S3 and the underlying related diversification logic

Examples	Existing sectors	New emerging sectors	Activities to be prioritized	Related diversification logic
Development of nanotechnologies for the pulp and paper industry in Finland	Pulp and paper industry	Nano-technologies	Nano-technologies applied to pulp and paper industry	Modernization
Development of IT applications for the management of archaeological heritage in Italy (Florence)	Exploitation of archaeological and historical heritage	IT applications	IT applications for the management and maintenance of archaeological and historical heritage	Modernization[A1]
Plastics firms diversification from car industry to biomedical innovative applications, in Basque Country	Plastic sector applied to car industry	Plastic sector applied to biomedical applications	Diversification of the plastic sector towards biomedical applications	Transition
Transition, in Austria, from fine mechanical and optical engineering to medical technologies	Fine mechanical and optical engineering	Medical technologies	Transition from mechanical and optical engineering to medical technologies	Transition
Diversification of automotive subcontractors from the car industry to new sectors, in the British Midlands	Automotive subcontractors working for the car industry	Automotive subcontractors working for other industries	Exploring a transition path for automotive subcontractors from car industry towards new markets	Transition
Emergence, in Toulouse, of entrepreneurial activity in areas related to satellites and GPS technologies	Aeronautics (Airbus)	Satellites and GPS technologies	Development of Satellites and GPS technologies	Diversification

Source: Foray et al. (2012) and Foray (2013)

[A1] Although Foray et al. (2012) see this example as a case of 'radical foundation of a new domain', according to the logics of related diversification presented by Foray (2013) it seemed more appropriate to categorize this situation as a case of modernization.

Appendix B - Total number of patent applications per year

Year	Patents	Year	Patents	Year	Patents	Year	Patents	Year	Patents
1964	1	1981	16 260	1990	31 315	1999	60 254	2008	79 072
1966	1	1982	17 199	1991	31 305	2000	65 562	2009	78 024
1968	1	1983	19 519	1992	31 842	2001	66 182	2010	79 104
1969	2	1984	21 266	1993	33 216	2002	66 243	2011	80 388
1975	1	1985	23 224	1994	35 271	2003	68 626	2012	79 116
1977	2 286	1986	24 949	1995	37 216	2004	72 719	2013	76 555
1978	7 426	1987	28 434	1996	42 999	2005	75 793	2014	15 770
1979	11 753	1988	31 039	1997	48 775	2006	79 710	2015	11
1980	14 442	1989	32 355	1998	53 859	2007	83 065	**Total**	**1 722 152**

Source: OECD (2016) and author's computations

Appendix C - Total number of patent applications by IPC class and year

Year	Patents by IPC class	Year	Patents by IPC class	Year	Patents by IPC class	Year	Patents by IPC class	Year	Patents by IPC class
1964	1	1981	57 546	1990	118 194	1999	248 877	2008	199 285
1966	5	1982	60 976	1991	121 170	2000	276 198	2009	200 434
1968	3	1983	69 610	1992	121 837	2001	284 466	2010	207 914
1969	2	1984	78 454	1993	128 141	2002	264 376	2011	211 595
1975	2	1985	84 223	1994	137 515	2003	232 555	2012	205 630
1977	10 691	1986	92 290	1995	142 469	2004	218 491	2013	200 143
1978	29 397	1987	105 327	1996	163 162	2005	187 875	2014	41 728
1979	43 210	1988	114 214	1997	183 136	2006	195 841	2015	17
1980	52 444	1989	121 474	1998	209 823	2007	210 518	**Total**	**5 631 258**

Source: OECD (2016) and author's computations

Appendix D – Minimum, Median and Maximum by country – Static Indicator

Country	1990			2000			2013		
	min	median	max	min	median	max	min	median	max
Austria	0.09	0.48	0.77	0.35	0.61	0.85	0.21	0.62	0.95
Belgium	0.12	0.30	0.53	0.13	0.35	0.70	0.12	0.48	0.67
Bulgaria	0.04	0.05	0.06	0.00	0.06	0.36	0.03	0.08	0.26
Croatia	0.04	0.04	0.04	0.15	0.32	0.49	0.23	0.26	0.29
Cyprus	0.16	0.16	0.16	0.32	0.32	0.32	0.32	0.32	0.32
Czech Republic	0.13	0.13	0.13	0.07	0.18	0.28	0.08	0.29	0.47
Denmark	0.41	0.43	0.55	0.28	0.55	0.78	0.48	0.54	0.73
Estonia	-	-	-	0.17	0.17	0.17	0.34	0.34	0.34
Finland	0.45	0.56	0.66	0.06	0.56	0.94	0.03	0.60	0.75
France	0.00	0.55	0.72	0.08	0.51	0.80	0.04	0.48	0.85
Germany	0.07	0.57	1.00	0.31	0.59	1.00	0.32	0.57	0.92
Greece	0.04	0.07	0.31	0.04	0.11	0.32	0.02	0.07	0.49
Hungary	0.04	0.07	0.20	0.10	0.14	0.34	0.10	0.22	0.63
Iceland	0.07	0.07	0.07	0.19	0.20	0.20	0.13	0.19	0.25
Ireland	0.01	0.24	0.46	0.27	0.41	0.55	0.40	0.46	0.52
Italy	0.02	0.34	0.90	0.13	0.44	0.93	0.07	0.55	1.00
Latvia	-	-	-	0.22	0.22	0.22	0.49	0.49	0.49
Lichtenstein	0.68	0.68	0.68	0.66	0.66	0.66	0.45	0.45	0.45
Lithuania	-	-	-	0.09	0.09	0.09	0.46	0.46	0.46
Luxembourg	0.47	0.47	0.47	0.53	0.53	0.53	0.46	0.46	0.46
Malta	0.11	0.11	0.11	0.06	0.06	0.06	0.35	0.35	0.35
Netherlands	0.14	0.40	0.66	0.27	0.40	0.69	0.26	0.45	0.78
Norway	0.11	0.29	0.46	0.13	0.38	0.68	0.16	0.48	0.54
Poland	0.00	0.04	0.07	0.02	0.14	0.33	0.04	0.18	0.58
Portugal	0.02	0.04	0.07	0.12	0.17	0.24	0.02	0.19	0.46
Romania	0.04	0.04	0.04	0.04	0.11	0.18	0.01	0.07	0.28
Slovakia	0.04	0.04	0.04	0.10	0.14	0.17	0.00	0.22	0.39
Slovenia	0.13	0.13	0.13	0.24	0.35	0.46	0.42	0.49	0.55
Spain	0.00	0.13	0.63	0.09	0.35	0.71	0.15	0.47	0.84
Sweden	0.51	0.62	0.70	0.20	0.57	0.78	0.27	0.54	0.70
Switzerland	0.24	0.71	0.87	0.24	0.46	0.86	0.26	0.53	0.72
United Kingdom	0.12	0.44	0.67	0.14	0.44	0.73	0.19	0.50	0.77

Source: author's computations

Appendix E - Percentage of regions, by country, with above-median static indicator (2013)

Country	Number of Regions (%)	Country	Number of Regions (%)	Country	Number of Regions (%)	Country	Number of Regions (%)
Bulgaria	0 %	Portugal	0 %	Netherlands	50 %	Sweden	63 %
Croatia	0 %	Romania	0 %	Slovenia	50 %	Belgium	64 %
Cyprus	0 %	Slovakia	0 %	Spain	53 %	Germany	74 %
Estonia	0 %	Czech Republic	13 %	United Kingdom	57 %	Austria	78 %
Iceland	0 %	Hungary	14 %	Italy	57 %	Switzerland	86 %
Lichtenstein	0 %	Greece	17 %	Norway	57 %	Denmark	100 %
Luxembourg	0 %	Poland	19 %	Finland	60 %	Lithuania	100 %
Malta	0 %	Ireland	50 %	France	61 %	Latvia	100 %

Source: author's computations

Appendix F – Regions by category

	S3 Persistent Leaders		
Region code	**Region name**	**Static indicator - 2000**	**Static indicator - 2013**
AT12	NIEDERÖSTERREICH	0.73	0.71
AT21	KÄRNTEN	0.53	0.53
AT22	STEIERMARK	0.79	0.76
AT31	OBERÖSTERREICH	0.85	0.95
AT32	SALZBURG	0.56	0.62
AT33	TIROL	0.68	0.66
AT34	VORARLBERG	0.61	0.42
BE10	RÉGION DE BRUXELLES-CAPITALE / BRUSSELS HOOFDSTEDELIJK GEWEST	0.46	0.48
BE25	PROV. WEST-VLAANDEREN	0.70	0.67
BE33	PROV. LIÈGE	0.68	0.49
CH02	ESPACE MITTELLAND	0.71	0.46
CH04	ZÜRICH	0.46	0.47
CH05	OSTSCHWEIZ	0.86	0.72
CH06	ZENTRALSCHWEIZ	0.59	0.66
CH07	TICINO	0.44	0.58
DE11	STUTTGART	0.75	0.79
DE12	KARLSRUHE	0.75	0.91
DE13	FREIBURG	0.62	0.67
DE14	TÜBINGEN	0.88	0.72
DE21	OBERBAYERN	0.65	0.69
DE22	NIEDERBAYERN	0.57	0.74
DE24	OBERFRANKEN	0.61	0.92
DE26	UNTERFRANKEN	0.56	0.62
DE27	SCHWABEN	0.95	0.77
DE40	BRANDENBURG	0.52	0.60
DE50	BREMEN	0.59	0.51
DE60	HAMBURG	0.50	0.50
DE71	DARMSTADT	0.53	0.44
DE72	GIEẞEN	0.70	0.54
DE73	KASSEL	0.67	0.57
DE91	BRAUNSCHWEIG	0.57	0.52
DE93	LÜNEBURG	0.60	0.49
DE94	WESER-EMS	0.96	0.81
DEA1	DÜSSELDORF	0.73	0.62
DEA3	MÜNSTER	0.81	0.61
DEA4	DETMOLD	0.85	0.70
DEA5	ARNSBERG	1.00	0.66
DEB1	KOBLENZ	0.82	0.84
DEC0	SAARLAND	0.54	0.57
DED2	DRESDEN	0.48	0.49
DED4	CHEMNITZ	0.58	0.51
DEE0	SACHSEN-ANHALT	0.55	0.55
DEF0	SCHLESWIG-HOLSTEIN	0.77	0.72
DEG0	THÜRINGEN	0.44	0.41
DK02	SJÆLLAND	0.43	0.48
DK03	SYDDANMARK	0.78	0.73
DK04	MIDTJYLLAND	0.67	0.70
DK05	NORDJYLLAND	0.55	0.54

ES21	PAÍS VASCO	0.59	0.68
ES24	ARAGÓN	0.46	0.56
ES30	COMUNIDAD DE MADRID	0.50	0.63
ES51	CATALUÑA	0.71	0.67
ES52	COMUNIDAD VALENCIANA	0.61	0.84
ES61	ANDALUCIA	0.45	0.70
FI19	LÄNSI-SUOMI	0.94	0.75
FI1C	ETELÄ-SUOMI	0.56	0.60
FI1D	POHJOIS- JA ITÄ-SUOMI	0.62	0.61
FR10	ÎLE DE FRANCE	0.43	0.39
FR21	CHAMPAGNE-ARDENNE	0.48	0.44
FR22	PICARDIE	0.71	0.39
FR23	HAUTE-NORMANDIE	0.50	0.42
FR24	CENTRE	0.71	0.56
FR26	BOURGOGNE	0.62	0.51
FR30	NORD - PAS-DE-CALAIS	0.69	0.50
FR41	LORRAINE	0.54	0.69
FR42	ALSACE	0.46	0.67
FR43	FRANCHE-COMTÉ	0.60	0.50
FR51	PAYS DE LA LOIRE	0.54	0.73
FR52	BRETAGNE	0.62	0.56
FR53	POITOU-CHARENTES	0.47	0.47
FR61	AQUITAINE	0.51	0.42
FR71	RHÔNE-ALPES	0.80	0.85
FR81	LANGUEDOC-ROUSSILLON	0.57	0.51
FR82	PROVENCE-ALPES-CÔTE D'AZUR	0.64	0.59
IE02	SOUTHERN AND EASTERN	0.55	0.52
ITC1	PIEMONTE	0.84	0.99
ITC3	LIGURIA	0.49	0.55
ITC4	LOMBARDIA	0.88	0.79
ITH1	PROVINCIA AUTONOMA DI BOLZANO/BOZEN	0.46	0.59
ITH2	PROVINCIA AUTONOMA DI TRENTO	0.44	0.71
ITH3	VENETO	0.93	1.00
ITH4	FRIULI-VENEZIA GIULIA	0.67	0.68
ITH5	EMILIA-ROMAGNA	0.90	0.80
ITI1	TOSCANA	0.67	0.66
ITI3	MARCHE	0.70	0.66
LI00	LIECHTENSTEIN	0.66	0.45
LU00	LUXEMBOURG (GRAND-DUCHÉ)	0.53	0.46
NL21	OVERIJSSEL	0.69	0.50
NL22	GELDERLAND	0.55	0.78
NL31	UTRECHT	0.51	0.54
NL32	NOORD-HOLLAND	0.53	0.65
NL33	ZUID-HOLLAND	0.50	0.54
NL42	LIMBURG (NL)	0.44	0.40
NO01	OSLO OG AKERSHUS	0.62	0.52
NO03	SØR-ØSTLANDET	0.68	0.49
NO04	AGDER OG ROGALAND	0.56	0.48
SE12	ÖSTRA MELLANSVERIGE	0.57	0.61
SE21	SMÅLAND MED ÖARNA	0.60	0.63
SE22	SYDSVERIGE	0.57	0.70
SE31	NORRA MELLANSVERIGE	0.78	0.44
SE33	ÖVRE NORRLAND	0.55	0.58
SI02	ZAHODNA SLOVENIJA	0.46	0.42

Region code	Region name		
UKC2	NORTHUMBERLAND AND TYNE AND WEAR	0.50	0.50
UKD3	GREATER MANCHESTER	0.52	0.45
UKD4	LANCASHIRE	0.48	0.52
UKD6	CHESHIRE	0.45	0.51
UKE3	SOUTH YORKSHIRE	0.50	0.46
UKE4	WEST YORKSHIRE	0.48	0.39
UKF1	DERBYSHIRE AND NOTTINGHAMSHIRE	0.52	0.59
UKF2	LEICESTERSHIRE, RUTLAND AND NORTHAMPTONSHIRE	0.62	0.50
UKG1	HEREFORDSHIRE, WORCESTERSHIRE AND WARWICKSHIRE	0.62	0.52
UKG2	SHROPSHIRE AND STAFFORDSHIRE	0.67	0.77
UKG3	WEST MIDLANDS	0.65	0.51
UKH1	EAST ANGLIA	0.44	0.55
UKH3	ESSEX	0.54	0.57
UKJ3	HAMPSHIRE AND ISLE OF WIGHT	0.67	0.66
UKK1	GLOUCESTERSHIRE, WILTSHIRE AND BRISTOL/BATH AREA	0.49	0.53
UKK2	DORSET AND SOMERSET	0.57	0.45
UKL1	WEST WALES AND THE VALLEYS	0.73	0.51
UKL2	EAST WALES	0.54	0.43
UKM2	EASTERN SCOTLAND	0.57	0.67

S3 Recent Leaders

Region code	Region name	Static indicator - 2000	Static indicator - 2013
AT13	WIEN	0.40	0.53
BE21	PROV. ANTWERPEN	0.25	0.39
BE22	PROV. LIMBURG (B)	0.34	0.48
BE23	PROV. OOST-VLAANDEREN	0.35	0.62
BE24	PROV. VLAAMS-BRABANT	0.38	0.44
BE31	PROV. BRABANT WALLON	0.26	0.48
BE32	PROV. HAINAUT	0.41	0.47
CH01	RÉGION LÉMANIQUE	0.38	0.53
CZ05	SEVEROVYCHOD	0.27	0.40
CZ07	STREDNI MORAVA	0.22	0.47
DE30	BERLIN	0.31	0.39
DEA2	KÖLN	0.37	0.59
DED5	LEIPZIG	0.42	0.43
DK01	HOVEDSTADEN	0.28	0.53
EL30	ATTIKI	0.32	0.49
ES11	GALICIA	0.18	0.61
ES22	COMUNIDAD FORAL DE NAVARRA	0.36	0.42
ES41	CASTILLA Y LEÓN	0.37	0.47
ES42	CASTILLA-LA MANCHA	0.13	0.52
ES70	CANARIAS	0.35	0.42
FR25	BASSE-NORMANDIE	0.27	0.48
FR62	MIDI-PYRÉNÉES	0.34	0.48
HU10	KOZEP-MAGYARORSZAG	0.34	0.63
IE01	BORDER, MIDLAND AND WESTERN	0.27	0.40
ITF1	ABRUZZO	0.28	0.41
ITF3	CAMPANIA	0.42	0.42
ITF4	PUGLIA	0.32	0.49
ITI2	UMBRIA	0.32	0.42
ITI4	LAZIO	0.35	0.68
LT00	LIETUVA	0.09	0.46
LV00	LATVIJA	0.22	0.49

Region code	Region name	Static indicator - 2000	Static indicator - 2013
NL12	FRIESLAND (NL)	0.35	0.48
NL23	FLEVOLAND	0.31	0.42
NO05	VESTLANDET	0.38	0.54
NO06	TRØNDELAG	0.33	0.45
PL12	MAZOWIECKIE	0.33	0.58
PL21	MALOPOLSKIE	0.11	0.56
PL22	SLASKIE	0.21	0.57
PL41	WIELKOPOLSKIE	0.15	0.41
PT11	NORTE	0.17	0.46
PT17	LISBOA	0.24	0.41
SE32	MELLERSTA NORRLAND	0.40	0.50
SI01	VZHODNA SLOVENIJA	0.24	0.55
SK01	BRATISLAVSKY KRAJ	0.17	0.39
UKE2	NORTH YORKSHIRE	0.38	0.49
UKH2	BEDFORDSHIRE AND HERTFORDSHIRE	0.34	0.54
UKI1	INNER LONDON	0.42	0.44
UKI2	OUTER LONDON	0.16	0.61
UKJ1	BERKSHIRE, BUCKINGHAMSHIRE AND OXFORDSHIRE	0.31	0.41
UKJ2	SURREY, EAST AND WEST SUSSEX	0.41	0.54
UKJ4	KENT	0.34	0.40
UKK4	DEVON	0.40	0.42
UKM3	SOUTH WESTERN SCOTLAND	0.38	0.54
UKN0	NORTHERN IRELAND	0.41	0.68

S3 Persistent Followers

Region code	Region name	Static indicator - 2000	Static indicator - 2013
AT11	BURGENLAND (A)	0.35	0.21
BE34	PROV. LUXEMBOURG (B)	0.13	0.12
BE35	PROV. NAMUR	0.20	0.18
BG31	SEVEROZAPADEN	0.00	0.12
BG33	SEVEROIZTOCHEN	0.05	0.08
BG41	YUGOZAPADEN	0.36	0.26
BG42	YUZHEN TSENTRALEN	0.08	0.03
CH03	NORDWESTSCHWEIZ	0.24	0.26
CY00	KYPROS / KIBRIS	0.32	0.32
CZ01	PRAHA	0.28	0.29
CZ02	STREDNI CECHY	0.16	0.29
CZ03	JIHOZAPAD	0.09	0.20
CZ04	SEVEROZAPAD	0.07	0.08
CZ06	JIHOVYCHOD	0.20	0.35
CZ08	MORAVSKOSLEZSKO	0.12	0.24
DE80	MECKLENBURG-VORPOMMERN	0.42	0.33
DEB2	TRIER	0.39	0.35
DEB3	RHEINHESSEN-PFALZ	0.36	0.36
EE00	EESTI	0.17	0.34
EL12	KENTRIKI MAKEDONIA	0.15	0.23
EL43	KRITI	0.11	0.05
ES12	PRINCIPADO DE ASTURIAS	0.19	0.22
ES13	CANTABRIA	0.09	0.23
ES43	EXTREMADURA	0.10	0.19
ES53	ILLES BALEARS	0.24	0.30
ES62	REGIÓN DE MURCIA	0.16	0.36
FI1B	HELSINKI-UUSIMAA	0.42	0.35

Region code	Region name		
FI20	ÅLAND	0.06	0.03
FR63	LIMOUSIN	0.37	0.36
FR72	AUVERGNE	0.38	0.32
FR94	RÉUNION	0.08	0.15
HR03	JADRANSKA HRVATSKA	0.15	0.23
HU21	KOZEP-DUNANTUL	0.15	0.16
HU22	NYUGAT-DUNANTUL	0.11	0.11
HU23	DEL-DUNANTUL	0.10	0.26
HU31	ESZAK-MAGYARORSZAG	0.17	0.22
HU32	ESZAK-ALFOLD	0.11	0.10
HU33	DEL-ALFOLD	0.14	0.28
IS01	CAPITAL REGION	0.19	0.25
IS02	OTHER REGIONS	0.20	0.13
ITC2	VALLE D'AOSTA/VALLÉE D'AOSTE	0.17	0.15
ITF6	CALABRIA	0.13	0.17
ITG1	SICILIA	0.34	0.31
ITG2	SARDEGNA	0.19	0.25
MT00	MALTA	0.06	0.35
NL11	GRONINGEN	0.27	0.31
NL13	DRENTHE	0.28	0.26
NL34	ZEELAND	0.32	0.28
NL41	NOORD-BRABANT	0.37	0.31
NO02	HEDMARK OG OPPLAND	0.13	0.26
NO07	NORD-NORGE	0.23	0.16
PL11	LODZKIE	0.14	0.27
PL31	LUBELSKIE	0.02	0.04
PL32	PODKARPACKIE	0.05	0.16
PL42	ZACHODNIOPOMORSKIE	0.13	0.16
PL51	DOLNOSLASKIE	0.17	0.37
PL52	OPOLSKIE	0.07	0.14
PL62	WARMINSKO-MAZURSKIE	0.05	0.09
PL63	POMORSKIE	0.21	0.37
PT16	CENTRO (P)	0.16	0.34
PT30	REGIÃO AUTONOMA DA MADEIRA	0.12	0.02
RO22	SUD-EST	0.04	0.01
RO32	BUCURESTI - ILFOV	0.18	0.28
SE11	STOCKHOLM	0.20	0.27
SK02	ZAPADNE SLOVENSKO	0.10	0.32
SK03	STREDNE SLOVENSKO	0.16	0.00
SK04	VYCHODNE SLOVENSKO	0.11	0.11
UKC1	TEES VALLEY AND DURHAM	0.31	0.34
UKD1	CUMBRIA	0.35	0.29
UKD7	MERSEYSIDE	0.41	0.36
UKE1	EAST YORKSHIRE AND NORTHERN LINCOLNSHIRE	0.23	0.35
UKF3	LINCOLNSHIRE	0.21	0.32
UKK3	CORNWALL AND ISLES OF SCILLY	0.35	0.19
UKM5	NORTH EASTERN SCOTLAND	0.38	0.33
UKM6	HIGHLANDS AND ISLANDS	0.14	0.22

S3 Recent Followers

Region code	Region name	Static indicator - 2000	Static indicator - 2013
DE23	OBERPFALZ	0.55	0.32
DE25	MITTELFRANKEN	0.78	0.38

DE92	HANNOVER	0.45	0.36
HR04	KONTINENTALNA HRVATSKA	0.49	0.29
SE23	VÄSTSVERIGE	0.71	0.36

Appendix G – Percentage distribution of regions according to categories, by country

Countries	S3 persistent leaders	S3 recent leaders	S3 persistent followers	S3 recent followers	N regions
Austria	78 %	11 %	11 %	0 %	9
Belgium	27 %	55 %	18 %	0 %	11
Bulgaria	0 %	0 %	100 %	0 %	4
Croatia	0 %	0 %	50 %	50 %	2
Cyprus	0 %	0 %	100 %	0 %	1
Czech Republic	0 %	25 %	75 %	0 %	8
Denmark	80 %	20 %	0 %	0 %	5
Estonia	0 %	0 %	100 %	0 %	1
Finland	60 %	0 %	40 %	0 %	5
France	77 %	9 %	14 %	0 %	22
Germany	76 %	8 %	8 %	8 %	38
Greece	0 %	33 %	67 %	0 %	3
Hungary	0 %	14 %	86 %	0 %	7
Iceland	0 %	0 %	100 %	0 %	2
Ireland	50 %	50 %	0 %	0 %	2
Italy	53 %	26 %	21 %	0 %	19
Latvia	0 %	100 %	0 %	0 %	1
Lichtenstein	100 %	0 %	0 %	0 %	1
Lithuania	0 %	100 %	0 %	0 %	1
Luxembourg	100 %	0 %	0 %	0 %	1
Malta	0 %	0 %	100 %	0 %	1
Netherlands	50 %	17 %	33 %	0 %	12
Norway	43 %	29 %	29 %	0 %	7
Poland	0 %	33 %	67 %	0 %	12
Portugal	0 %	50 %	50 %	0 %	4
Romania	0 %	0 %	100 %	0 %	2
Slovakia	0 %	25 %	75 %	0 %	4
Slovenia	50 %	50 %	0 %	0 %	2
Spain	38 %	31 %	31 %	0 %	16
Sweden	63 %	13 %	13 %	13 %	8
Switzerland	71 %	14 %	14 %	0 %	7
United Kingdom	51 %	27 %	22 %	0 %	37

Source: author's computations