Evidence-driven decision making in smart specialisation strategies: A patent-based approach for discovering regional technological capabilities

Abstract

Discovering regional technological capabilities is key to underpinning the place-based and evidence-driven logic of smart specialisation. However, a comprehensive methodological approach for operationalizing the mapping, assessment, and benchmarking of regional technological knowledge is urgently required. To address this need, we design and test a patent-based methodology, which helps to profile technological domains in EU regions, detects technological competitive advantages and opportunities for knowledge recombination, assesses selected S3 priorities against regional innovation performance measures, and conducts benchmarking activities. This study lays the foundation for tailoring a digital application, to complement the suite of online services for S3 development currently available.

Keywords: *Smart specialisation; regional innovation; technological profiling; regional technological capabilities; patent-based methodology*

1. Introduction

The analysis of emergent technological sectors is a key activity underpinning the place-based and evidence-driven logic of the smart specialisation approach (Correa and Güçeri, 2016; Vezzani et al., 2017). Technological analysis allows regional and national governments to profile their technological competences, detect priority areas of investment, and support the knowledge discovery process that Research and Innovation Strategies for Smart Specialisation (RIS3) advocate for. It also allows them to conduct benchmarking exercises and establish evidence-informed collaborative partnerships (Foray, 2014; Piirainen et al., 2017). However, in spite of the relevance of and urgent need for a comprehensive methodological approach for operationalising the mapping, assessment, and benchmarking of technological knowledge at the regional level, regional studies literature investigating this matter has been relatively scant, with a few notable exceptions (Ciffolilli and Muscio, 2018; D'Adda et al., 2019; Komninos et al., 2018a).

We contribute to addressing this research gap by designing and testing a methodology for discovering regional technological capabilities, whose implementation can assist in developing the evidence base required to inform smart specialisation strategy (S3) formulation. This methodology leverages patent data and patent-based indicators to assist in: profiling technological domains in EU regions; assembling a graphical representation of these profiles; detecting competitive advantages and potential opportunities for knowledge recombination; assessing the alignment between selected S3 priorities and regional innovation performance measures; and supporting cross-regional benchmarking activities.

In this study, we assemble the proposed methodology and test its practical feasibility, effectiveness, and operability by deploying four EU regions registered in the S3 Platform as testbeds. South-West Oltenia (Romania), Lombardy (Italy), the Walloon Region (Belgium), and Central Jutland (Denmark) are the regions selected for conducting this pilot study, which begins with the collection of patent data. A database is built, which collates all data on patents developed by inventors residing in the four pilot regions, whose application date falls between 2014 and 2019. This data is sourced from the United States Patent and Trademark Office (USPTO) database. A set of key indicators used in patent analysis are then applied to profile technological capabilities. These indicators inform on the knowledge stock embedded in EU regions. Additionally, patent-based indicators are also used to assess the alignment between selected S3 priorities and the actual regional innovation performance.

The paper adopts the following structure. The following section exposes the significance of outlining technological capabilities in the RIS3 context and the role that our methodology can play in tackling the design and implementation issues affecting S3 practice. The third section of the paper introduces such a methodology, whose functionality is subsequently tested in the fourth section. The last section of the paper expands on the theoretical and practical implications of this study and details its limitations.

2. Literature review

Strategies for smart specialisation represent prioritisation agendas for supporting regional innovation policy development and result from the connection between non-spatial innovation policy debate and the European Cohesion Policy (McCann and Ortega-Argilés, 2013). The paradigm shift underpinning S3 lies in the combination between a place-based approach to regional innovation paths, which *"strongly depend on territorial elements rooted in the local society, its history, its culture, and its typical learning processes"* (Camagni et al., 2014: 72), and a policy-prioritisation logic that *"explicitly avoids automatically prioritizing high-*

technology sectors by taking a broader systems perspective" (McCann and Ortega-Argilés, 2015: 1293).

The smart specialisation approach demonstrates the commitment of the European Commission towards constantly enhancing the procedure for programming and allocating Structural Funds. This upgrade is premised on the benefits of adopting a prioritisation logic that builds on the evidence-based potential for research and innovation excellence in EU regions. Strategies for smart specialisation promise improved regional innovation processes, yet this policymaking approach has struggled to deliver on the expectations. The limited methodological guidance offered by the European Commission on how S3 should be crafted (Foray et al., 2012; Gianelle et al., 2016), has left regional governments deprived of their power to act with confidence, undermining the capability of the smart specialisation process to lay the foundations for a European economic renewal (Boschma and Gianelle, 2014).

Without methodological advice, instead of bringing competitive advantage in an uncertain competitive landscape, policymaking in smart specialisation runs the risk of being tangled in one-size-fits-all policy discourses (Balland et al., 2019) or meeting public and private interests that are not necessarily linked to regional potential for innovation (Fotakis et al., 2014). This danger has triggered the reaction of academic institutions and research organisations operating in the RIS3 domain, whose research efforts have been instrumental in producing an initial set of supporting tools for S3 design and implementation. Most of these tools can be found in the S3 Platform (Kleibrink et al., 2014; McCann and Ortega-Argilés, 2016; Sörvik and Kleibrink, 2016) coordinated by the European Union's Joint Research Center, and the platform Online S3 (Komninos et al., 2018b), which has been assembled in the framework of a recently completed Horizon 2020 project.

In alignment with the RIS3 Guide (Foray et al., 2012), Online S3 breaks the formulation of smart specialisation policy statements in six complementary phases and provides a set of semi-automated digital services for knowledge-based policy development. The platform hosts 29 applications, which tap into a rich open-data environment and help regional and national European governments to: create synergies among RIS3 stakeholders; build cohesive governance systems stimulating collaborative leadership; analyse regional contexts to determine the potential for diversification and recombination; formulate shared visions of what future development paths should be pursued; select the mix of research and innovation priorities that can boost regional competitive advantage; design action plans for RIS3 implementation; monitor the progress, evaluate the results, and refine the existing strategy to increase performance (Komninos et al., 2018a; Komninos et al., 2018b).

As Foray (2019: 2074) notes, the main characteristic of S3 formulation is *"the combination between a planning logic and an entrepreneurial discovery logic"*, which respectively represent the top-down and bottom-up components of the S3 policy process. After completing the planning phase, which is expected to end with the selection of specific research and innovation priority areas, S3 development should continue with an ongoing Entrepreneurial Discovery Process (EDP). Interactive and inclusive bottom-up conversations among RIS3 stakeholders are conducted, to determine what collection of projects should be implemented to transform the selected priorities into regional competitive advantage (Santini et al., 2016). Diversification, relatedness, recombination, and knowledge complexity are the critical factors underpinning the EDP cycle (Crespo et al., 2017). Research has shown that regional economic renewal requires working towards reinforcing regional growth paths that build on diversification opportunities connected to new and more complex technological specialisation domains (Balland et al., 2019). This requires embracing a knowledge recombination approach (Griffith et al., 2017; Weitzman, 1998); the development paths of regional economies relate to local technological capabilities (Storper, 1995), and effective RIS3 are expected to profile such capabilities, evaluate their degree of relatedness, and recombine them in more complex knowledge-based settings that can forge competitive advantages (Boschma and Gianelle, 2014).

The RIS3 guide (Foray et al., 2012) and implementation handbook (Gianelle et al., 2016) released by the European Commission both advocate the importance of profiling technology-related competitive advantages in EU regions to increase S3 effectiveness, but they fall short of providing clear guidance on how to fulfil this exercise (Griniece et al., 2017; Iacobucci and Guzzini, 2016). Review of available S3 research reveals that, very few studies have attempted to overcome the lack of theoretically sound methodologies and supporting tools for guiding the selection and assessment of S3 priorities in light of existing regional technological competences (Balland et al., 2019; D'Adda et al., 2019; Santoalha, 2019). As a result, EU regions still need to be supported regarding this dilemma (Balland et al., 2019).

A research stream has developed which suggests that related variety measures at the industry level are useful instruments for evaluating regional diversification and specialisation (Frenken et al., 2007; Van Oort et al., 2015). However, since these measures are focused on industry classification codes, they can capture commonalities across different industries but fail to map

relevant technological development paths within regional territories. Other indicators to assess regional diversification, which are based on commonalities between sectors, such as the cross-industry labour flows (Neffke and Henning, 2013), suffer from the same disadvantage.
Considering this gap and building on the aforementioned S3 literature, we suggest studying regional technological capabilities by adopting patent-based measures. Despite some limitations[1], patent-based measures have proven accurate in discovering regional patterns of technological evolution (Ardito et al., 2018; Lee and Lee, 2013) and assessing selected S3 priorities by analysing the actual output of innovative activities embedded in regional territories (D'Adda et al., 2019; Santoalha, 2019). This capability is evidenced in studies examining S3 development by means of patent analysis. However, methodological approaches for outlining and analysing the technological profile of regions have yet to be assembled. For example, patent data has been used to proxy the technological capabilities of regions and support foresight (Piirainen et al., 2017). In addition, some initial attempts have been made to leverage patent data to verify whether the strategies for smart specialisation which EU regions have designed, are in alignment with their innovative capabilities (Balland et al., 2019; D'Adda et al., 2019; Santoalha, 2019). Of particular interest is the recent work by D'Adda et al. (2019), which leverages patent data to assess the coherence between the technological domains selected by Italian regions in the S3 formulation process and their technological capabilities. This research activity represents a seminal contribution to the patent-based methodology that we propose for discovering regional technological capabilities.

3. Data and methodology

In light of the current knowledge gap and the possibilities that patent-based indicators offer to informed strategy formulation in smart specialisation development (Capello and Kroll, 2016; Fischer et al., 2019), a three-stage methodology was assembled, which allowed the researchers to profile the technological capabilities of EU regions, helped to detect opportunities for enhancing regional competitive advantage by means of knowledge recombination initiatives, and inform the selection of S3 priorities.

[1] Some technological developments may be overlooked because not all inventions are patented (Zuniga et al., 2009). Additionally, there is some time-lag between the R&D effort and the subsequent patent application, which may limit the timeliness of the measures (Kondo, 1999). Finally, different propensities to patent may characterise distinct technological sectors and geographical areas (Albino et al., 2014), but this can be mitigated by using relative measures.

3.1. Stage 1: Patent data collection

The analysis begins with a data collection phase. Our methodology leverages patent indicators to detect and analyse regional technological trends (Jacobsson and Philipson, 1996; Rocchetta and Mina, 2019). Patents and their International Patent Classification (IPC) system represent a rich data source for examining innovation processes and technological evolution (Jaffe and Trajtenberg, 2002) within countries and regions (Iversen, 2000). Patent data can be sourced from a number of databases; however, when the objective is to determine regional technological capabilities, we recommend adopting the USPTO database. Unlike other patent offices, USPTO provides very clear and detailed information about the geographic location of the inventor, making it possible to easily search for, extract, and analyse patented technologies developed in EU regions, with the highest level of granularity. Additionally, USPTO clearly indicates backward and forward patent citations, which are paramount to apply the proposed methodology. The USPTO database is also one of the world's largest repositories of patent documents and has the highest resident to non-resident ratio of applications (Kim and Lee, 2015). These features suggest that this database is particularly effective for performing comprehensive cross-region analyses of technological capabilities.

3.2. Stage 2: Technological profiles

After collecting the necessary patent data, the technology-related competitive advantages of EU regions and their potential opportunities for knowledge recombination can be examined. The following set of indicators is assembled to build regional technological profiles, that can be easily visualised and compared using graphical methods. These indicators are based on patent data and are considered the most suitable for tracing regional technological capabilities. They were selected based on insight offered by available literature on patent-portfolio analyses (Ernst, 2003; Jaffe and Trajtenberg, 2002) and regional-level patent-based analyses (Iversen, 2000; Jacobsson and Philipson, 1996; Kogler et al., 2017). These indicators help capture the existing technological knowledge base of EU regions and produce the insight needed to inform the S3 priority selection process, ensuring that S3 development truly embraces a location-based perspective (Camagni et al., 2014). This methodology strengthens the idea that strategies for smart specialisation are not one-size-fits-all policies for regional growth, and differences in technological knowledge should be reflected in the selection of S3 priorities (Foray, 2019).

Accordingly, defining regional technological profiles and examining technological relatedness is crucial in guiding S3 development.

The first indicator we propose uncovers the linkages between patented technologies and scientific knowledge (*SciKnowledge*). This connection is evaluated by relying on the non-patent backward citations, as listed in the focal region's patents. These citations represent the scientific knowledge leveraged in the patent development process (Callaert et al., 2006). Therefore, *SciKnowledge* for a specific region is calculated as:

$$SciKnowledge = \frac{\sum_j WeightedNPCitations_j}{PAT}$$

where *PAT* denotes the total number of patents associated with the selected region, whereas $WeightedNPCitations_j$ represents the weighted number of non-patent backward citations of the j-th patent related to such a region. Following the method proposed by Hall et al. (2001), we suggest creating cohorts of patents which aggregate USPTO-registered European patents, showing identical main IPC technological class and application year. The average number of non-patent backward citations is calculated for each cohort, and the $WeightedNPCitations_j$ is computed as the ratio between the number of non-patent backward citations of the j-th patent and the average value of its cohort. This approach makes it possible to obtain comparable measures, which allow for cross-year comparison and where regional economic diversification is properly taken into account.

An informative technological profile needs to show the extent of the pioneering nature of the technology developed (*Pioneering*) (Nerkar and Shane, 2007). Pioneering technologies significantly diverge from current technological solutions and may suggest a shift in technological progress, by creating new innovation pathways (Ahuja and Morris Lampert, 2001). We measure *Pioneering* as the average number of backward citations of a region's patents:

$$Pioneering = \frac{\sum_j WeightedBackwCit_j}{PAT}$$

where $WeightedBackwCit_j$ denotes the weighted number of backward citations of the j-th patent belonging to the selected region — calculated by adopting the cohort method proposed by Hall et al. (2001). It should be noted that this indicator is inversely coded (Nerkar and Shane, 2007);

hence, a high value of the indicator suggests that regional technologies are strongly linked to previous technological solutions.

Moreover, we propose to evaluate the technological impact of a region's patents by using *TechImpact*. To measure this indicator, we use the forward citations received by the focal patents, which are largely recognised in the scientific literature as being related to the extent of technological progress spurred from such patents (e.g. Trajtenberg, 1990). Considering that forward citations are influenced by the time elapsed since a patent had been first disclosed (Hall et al., 2001), the weighted forward citations received annually by each patent since its application, should be averaged by the number of patents belonging to a specific region. This mathematical calculation is described in the following formula:

$$TechImpact = \frac{\sum_j WeightedForwCit_j}{PAT}$$

where $WeightedForwCit_j$ denotes the number of forward citations received by the j-th patent referring to a region — weighted using the cohort method by Hall et al. (2001) — from the date of the j-th patent application to the retrieval of its forward patents from the selected database. In this way, we take into account the truncation of forward patent citations, which is caused by the presence of patents applied for in different years (Hall et al., 2001).

In our methodology, we also consider the degree of generality of the technologies developed in a region, which describes their suitability for application in multiple domains and potential technology development in different industrial sectors (Bresnahan and Trajtenberg, 1995). The value of technological generality (*TechGenerality*) is calculated by applying the measure defined by Hall et al. (2001), which is based on the Herfindahl-Hirschman index (HHI). However, in this case, the unit of analysis is a region, rather than a single patent. Additionally, to avoid bias in the analysis of regions characterised by a low number of forward citations, the correction factor suggested by Hall (2005) is adopted. Accordingly, we measured technological generality as:

$$TechGenerality = \frac{ForwCit}{ForwCit - 1}\left[1 - \sum_k \left(\frac{ForwCit_k}{ForwCit}\right)^2\right]$$

where *ForwCit* denotes the overall number of forward citations received from a region's patents and $ForwCit_k$ denotes the number of forward citations received by the patents of the region in the k-th IPC technological class[2].

Technological generality measures are complemented with an indicator focused on the search breadth (*SearchBreadth*), which is based on the patents' backward citations. This indicator is used to evaluate the breadth of the range of domains that inventors leveraged to develop the focal technologies and is based on the HHI of the backward citations' technological classes (Hall et al., 2001), including a correction factor to avoid bias, due to the presumably low number of backward citations (Hall, 2005). *SearchBreadth* is measured as follows:

$$SearchBreadth = \frac{BackwCit}{BackwCit - 1}\left[1 - \sum\nolimits_k \left(\frac{BackwCit_k}{BackwCit}\right)^2\right]$$

where *BackwCit* represents the overall number of backward citations made by the patents of a region and $BackwCit_k$ denotes the number of backward citations made by the same patents in the k-th IPC technological class[3].

The following indicator (*TechDiv*) defines the range of technical areas where a region has technological competences (Granstrand and Oskarsson, 1994). This measure uses the HHI of the technological classes of the focal patents (Garcia-Vega, 2006; Natalicchio et al., 2017):

$$TechDiv = 1 - \sum\nolimits_k \left(\frac{PatClass_k}{PAT}\right)^2$$

where $PatClass_k$ denotes the number of patents belonging to a region and reporting the k-th IPC technological class.

To detect potential opportunities for knowledge recombination, we recommend calculating the average technological relatedness (*AverageTechRel*) with the approach proposed by Kogler et al. (2017):

$$AverageTechRel = \frac{\sum_i \sum_j S_{ij} * (N_i * N_{j)} + \sum_i 2N_i}{P * (P - 1)}, for\ i \neq j$$

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[2] For *TechGenerality* and the following three indicators, the first four digits of the IPC technological classes were used.

[3] For *TechGenerality* and *SearchBreadth*, we did not weigh the forward and backward citations, respectively, because this action could introduce bias in the information offered by both indicators.

Considering a specific time period, N_i and N_j represent the numbers of patents that a region has applied for in the i-th and j-th IPC technological classes, respectively, and P denotes the total number of patents that a region has applied for. Finally, S_{ij} denotes the technological proximity (also referred to as knowledge relatedness) between the i-th and j-th IPC technological classes, which is measured as:

$$S_{ij} = \frac{N_{ij}}{\sqrt{N_i * N_j}}$$

where N_{ij} represents the number of patents applied by a region and jointly related to both the i-th and the j-th IPC technological classes for the selected time frame.
It is important to highlight that the average technological relatedness should be calculated for the whole technological portfolio of a region. A high *AverageTechRel* value indicates relative specialisation; the technological knowledge production of a region is characterised by a limited co-occurrence of different IPC classes. On the contrary, a low value suggests a higher diversification, because the technological knowledge developed by a region covers a higher number of different couples of IPC technological classes (Kogler et al., 2017).

3.3. Stage 3: S3 priorities assessment

After building the technological profile of a region, the alignment between its S3 priorities and actual regional innovation performance can be assessed, generating opportunities for cross-regional benchmarking. This activity requires matching the IPC technological classes with the regional S3 priorities, as encoded in the Eye@RIS3 tool. For each S3 priority, a group of keywords describing the main technological field should be selected and used to identify the most closely related technological classes from the IPC database. This identification process, especially for complex and multifaceted S3 priorities, may require the participation of patent experts to define the keywords associated with the priorities and find a match with the IPC technological classes (Noailly and Batrakova, 2010). However, existing classification systems matching IPC technological classes with specific technological fields can also be exploited, such as the IPC Green Inventory (Albino et al., 2014) or the "J tag" developed by the OECD to classify information and communication technologies (Inaba and Squicciarini, 2017).

The first indicator we recommend for calculation is the overall number of assigned patents for the i-th S3 priority (*PATi*), on the basis of the identified technological classes. This value helps evaluate the development of technological knowledge related to a S3 priority in absolute terms and assess its overall importance for the region. Moreover, this data supports the benchmarking process, by avoiding biased interpretations due to sensitive differences in the number of patents assigned to a specific priority.

Afterwards, we propose to measure the focalisation of a region on the i-th S3 priority ($PriorityIntensity_i$) by calculating the ratio between PAT_i and the overall number of patents developed in the same region (*PAT*):

$$PriorityIntensity_i = \frac{PAT_i}{PAT}$$

This indicator allows specialisation to be evaluated in relative terms at the regional level, and it highlights the importance of the S3 priorities for any selected region (Ernst, 2003).

Alongside this indicator, to provide a more comprehensive picture, the Relative Technological Advantage (RTA) is calculated. The RTA is based on the Balassa Index (Balassa, 1963), which captures the degree of specialisation for a region in a defined technological field. This measure can be easily compared among regions (e.g. EU regions registered in the S3 platform) (Debackere et al., 1999). The RTA shows whether a region has a technological advantage in a specific field, with respect to the average specialisation of all the regions operating in such a technological field. Accordingly, the RTA for a region in the i-th S3 priority (RTA_i) is calculated as follows:

$$RTA_i = \frac{\left(\frac{PAT_i}{PAT}\right)}{\left(\frac{OvrPAT_i}{OvrPAT}\right)}$$

where $OvrPAT_i$ is the overall number of patents of all the regions included in the analysis and referring to the i-th S3 priority, and *OvrPAT* is the overall number of patents of the same regions. Furthermore, since RTA is strongly asymmetrical, we normalise the indicator for a region in the i-th priority ($RSTA_i$) as it follows (Dalum et al., 1998):

$$RSTA_i = \frac{RTA_i - 1}{RTA_i + 1}$$

A value of $RSTA_i$ higher than 0 represents a strong position in the i-th technological field, while a value lower than 0 indicates a weak position (Dalum et al., 1998; D'Adda et al., 2019).

4. Results of the pilot study

A pilot study was conducted to illustrate the practical feasibility and effectiveness of the proposed methodology. Four pilot EU regions were selected from the S3 Platform (see Table 1). During the selection process, two main criteria were considered. Firstly, to test whether differences in innovation performance affect the functioning of the proposed methodology, the selected regions belong to countries with different innovation performances (see Balland et al., 2019). The information required to assess the innovation performance was sourced from the European Innovation Scoreboard (EIS), where regions are clustered in four categories (Hollanders et al., 2019). We selected a pilot region from each category. Secondly, regions with similar S3 priorities — as encoded in the Eye@RIS3 tool — were preferred, enabling benchmarking to form a component of the study. Accordingly, South-West Oltenia (Romania), Lombardy (Italy), the Walloon Region (Belgium), and Central Jutland (Denmark) were selected as pilot regions.

	South-West Oltenia Romania	**Lombardy** Italy	**Walloon Region** Belgium	**Central Jutland** Denmark
Size (Km^2)	29,211.7	23,862.8	16,903.0	13,000.2
Population	2,220,224	9,992,548	3,603,439	1,266,682
National GDP (%)	8.03	21.31	23.40	20.64
Regional GERD[4] (%)	0.19	1.27	2.91	1.19
Analysed S3 priorities	Agriculture and Food Production; Energy and Climate	Agriculture and Food Production; Aeronautics and Space	Agriculture and Food Production; Aeronautics and Space	Agriculture and Food Production; Energy and Climate
Overall number of patents collected for the pilot study	25	2,601	606	549

Table 1. Overview of the four pilot regions. Data sourced from S3 Platform and USPTO. Demographic and economic data are updated to 2020.

[4] Gross domestic expenditure on research and development.

The *Agriculture and Food Production* priority is pursued by all regions, while the other priorities under investigation are also shared within the sample: *Aeronautics and Space* for Lombardy and the Walloon Region and *Energy and Climate* for South-West Oltenia and Central Jutland. The identification of the IPC classes associated with the S3 priorities is reported in Appendix A. In the cases of *Agriculture and Food Production* and *Aeronautics and Space*, a direct match between these priorities and the IPC classes was found (WIPO, 2015; 2019). The *Energy and Climate* priority was instead referred to the Alternative Energy Production topics of the IPC Green Inventory[5] that patent experts and the World Intellectual Property Organization (WIPO) have developed to classify environmentally sound technologies through IPC codes.

4.1. Stage 1: Patent data collection

To conduct the analysis, USPTO data was sourced to build a database in which all patents originating in the 28 EU Member States and filed between January 2014 and October 2019 were compiled. Since our methodology aimed to inform strategy formulation by assessing the actual technological performance of regions in the different S3 priority areas, we focused on the timeframe related to the first RIS3 design phase. Overall, the database contained 169,873 patents. After being collected, each patent document was assigned the relevant bibliographic data recorded in the USPTO database. This information included titles, filing dates, issue dates, backward and forward citations, technological classes, and all inventor details (i.e. full name, city, and country of residence).

Inventor details made it possible to match the patents to the 172 EU regions registered in the S3 Platform. This task aimed to establish where the technological knowledge linked to the patented material was embedded, by matching the inventors' city of residence with the European region to which it belonged. The matching was performed by sourcing data from the national institutes of statistics and public geographic databases, such as Google Maps. While conducting this activity, a number of ambiguous cases surfaced which were removed to avoid bias: inventors whose allocation to a specific region was prevented, due to the presence of cities with identical names within the same country. As a result of the matching process, the initial database was expanded with 414,041 inventor-patent couples.

[5] Available at: https://www.wipo.int/classifications/ipc/en/green_inventory/

4.2. Stage 2: Technological profiles

The patent data related to the four pilot regions, which accounted for 3,781 patents, were then selected to outline the technological profiles. The profiles are detailed in Table 2 and presented in Figure 1.

	South-West Oltenia	Lombardy	Walloon Region	Central Jutland
SciKnowledge	1.47	0.56	0.79	0.67
Pioneering	1.91	0.81	2.10	0.70
TechImpact	0.47	0.38	0.31	0.30
TechGenerality	0.82	0.96	0.96	0.95
SearchBreadth	0.84	0.96	0.92	0.97
TechDiv	0.87	0.97	0.98	0.97
AverageTechRel	0.92	0.06	0.11	0.12

Table 2. Technological profiles of each region

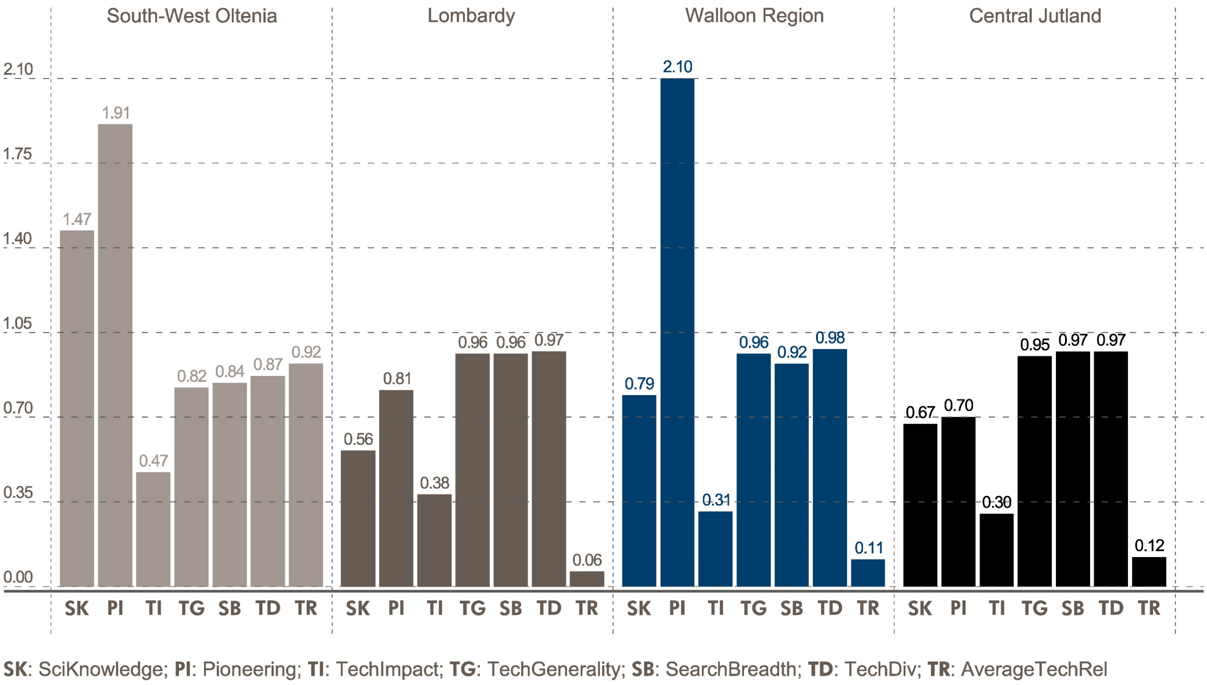

Figure 1. Regional technological profiles

The technological profiles of the four pilot regions indicate the presence of heterogeneity, that may affect the benefits they receive from S3 implementation (Foray, 2019). For instance, the profile of South-West Oltenia indicates that the region develops patents focused on specific technological domains, suggesting that it may follow a dependency path, as confirmed by the *TechDiv*, *TechGenerality*, and *SearchBreadth* indicators. Moreover, these developed technologies highly rely on scientific knowledge and previous technological knowledge, and show a high impact. Regions with profiles similar to South-West Oltenia may find it difficult to adopt a knowledge recombination approach, due to a narrow focus on few technological domains. *AverageTechRel* corroborates these results; South-West Oltenia has the higher average technological relatedness among the pilot regions (0.92). This value suggests that its patents tend to focus on few and proximate technological classes, indicating high specialisation, which may conversely limit the opportunities for knowledge recombination and hinder the potential success of S3 implementation (Crespo et al., 2017). The cases of Lombardy, the Walloon Region, and Central Jutland are different; they show high values of *TechDiv*, *TechGenerality*, and *SearchBreadth*, thus highlighting that they own the potential for knowledge recombination. This result is confirmed by their average technological relatedness. Lombardy had the lowest *AverageTechRel* value among the four pilot regions (0.06); its technological knowledge production is diversified and covers several distant fields. In turn, this condition may increase the opportunity for knowledge recombination, generating positive effects on the value of the resulting technologies and paving the way for technological development in new and promising fields. Similarly, the Walloon Region and Central Jutland display values are equivalent to 0.11 and 0.12, respectively. Therefore, both regions are slightly more specialised than Lombardy, but still have high potential for knowledge recombination.

In addition, the results presented in Table 2 show that the technologies developed in Lombardy rely less on previous knowledge than those of South-West Oltenia, and their scientific content is low. However, these technologies have a moderate technological impact. Technologies developed in the Walloon Region seem to largely rely on previous scientific and technological knowledge. Moreover, as in the Lombardy case, these technologies are highly diversified, with high values of search breadth and technological generality, but the technological impact is relatively moderate. Finally, the technologies developed in Central Jutland are characterised by relatively low reliance on previous scientific and technological knowledge, while their impact is slightly lower than the other pilot regions. Therefore, the technologies developed in this region may be particularly novel, entailing some difficulties in being easily exploited accordingly to the S3 policy.

4.3. Stage 3: S3 priorities assessment

First, for each priority, we calculated the absolute number of patents registered by the four regions (Table 4). This information complements the relative measures discussed afterwards, providing additional insight into the analysis. Table 4 also reports the Priority Intensities and the RSTA values which have been measured to verify whether there is an alignment between the S3 priorities selected by the four pilot regions and their actual regional technological performance.

The results for South-West Oltenia suggest that the regional technological performance related to both the *Agriculture and Food Production* and *Energy and Climate* priorities is 0, because the region's absolute number of patents related to the field is 0, although these technological fields are indicated as priorities. However, as the analysis was performed using only USPTO data, it is possible that patents in these fields were filed at alternative patent offices. In this case, we would expect additional supporting evidence to be presented to support the selection of the proposed priority areas. In addition, Priority Intensity values confirm that Lombardy and the Walloon Region are actively operating in the S3 priorities they have selected. About 2-4% of the regional patents are filed in these technological fields. The results for Central Jutland are striking: 13.5% of the regional patents are filed in the *Agriculture and Food Production* sector, while for the *Energy and Climate* sector the value of the indicator is equal to 37.7%. This suggests that Central Jutland's research and development efforts are largely devoted to the latter sector.

To compare these figures with the average performance of all the regions registered in the S3 Platform, we calculated the RSTA indicator for the regions and the S3 priorities under investigation. In analysing the RSTA values, it is possible to establish whether a specific region is more (or less) specialised in a technological field, with respect to the EU regions in the S3 Platform. In particular, a RSTA value higher than 0 indicates that a region is more specialised in the technological field — compared to the average of the study sample — while a value lower than 0 suggests the opposite.

	Number of registered patents			**Priority Intensity**			**RSTA**		
	AFP	**AS**	**EC**	**AFP**	**AS**	**EC**	**AFP**	**AS**	**EC**
South-West Oltenia	0	-	0	0.000	-	0.000	-1.000	-	-1.000
Lombardy	73	72	-	0.028	0.028	-	-0.218	-0.325	-
Walloon Region	24	15	-	0.040	0.025	-	-0.049	-0.375	-

Central Jutland	74	-	207	0.135	-	0.377	0.510	-	0.743

Table 3. Regional technological performance: Number of registered patents, Priority Intensities and RTA for the Agriculture and Food Production (AFP), Aeronautics and Space (AS), and Energy and Climate (EC) priorities.

While the results for South-West Oltenia are not surprising for the reasons previously discussed, it should be noted that Lombardy has a RSTA lower than 0. This means that the specialisation of the region in the priorities analysed is below the average of the EU regions included in the S3 Platform. Nonetheless, it is noteworthy that the absolute number of patents related to Lombardy in the two fields is quite high with respect to the other pilot regions. The case of the Walloon Region is different; its performance in *Agriculture and Food Production* is barely below the average but, for the *Aeronautics and Space* priority, the indicator is significantly below the threshold level of 0, suggesting a weak technological advantage. Finally, the analysis of RSTA indicators provides additional emphasis on the performance of Central Jutland in the investigated priorities. In fact, the specialisation in the *Agriculture and Food Production* sector is higher than the threshold of 0, while in the *Energy and Climate* priority the region seems very specialised, with a RSTA of 0.743. This data suggests Central Jutland is an European leader in this sector.

5. Conclusions

This study offers both theoretical and practical contributions. First, it advances the current regional studies debate on smart specialisation, by expanding the theoretical understanding of how the inherent knowledge of regions can inform S3 design, implementation, and evaluation (Balland et al., 2019; D'Adda et al., 2019). Second, it improves the current conceptualisation of how statistics compiled from patent data can become knowledge indicators (Park and Park, 2006) and help measure technological innovation capability in territorial contexts (Basberg, 1987). This objective is achieved by positioning relevant measures of patent analysis in a different application domain - from the firm level to the regional context - and by proposing the adjustments required to ensure that such measures can be applied for regional study purposes. Third, our methodology for discovering regional technological capabilities improves the current practical understanding on how S3 formulation should unfold (Capello, 2014;

Capello and Kroll, 2016; Gianelle et al., 2016; Kroll, 2015; Reid et al., 2012), and it provides the basis for tailoring a digital application, to complement the suite of online services for S3 development that the Online S3 Platform and Smart Specialisation Platform offer. Our pilot study confirms the effectiveness of the proposed patent-based methodology, which can help detect technological capabilities across EU regions and enhance the quality of the context analysis phase that is required, to structure the evidence base supporting the selection of specialisation areas and subsequent activation of the EDP. The pilot study also shows that our methodology can be successfully deployed as a self-assessment tool for measuring the extent to which already selected S3 priorities are aligned with the actual regional innovation performance. As a result, S3 stakeholders can be kept *"informed and engaged in the policy cycle"* (Kleibrink et al., 2016: 1438) and provided with an accurate understanding of what logic of intervention should be followed to amend existing strategies (Gianelle and Kleibrink, 2015). These monitoring insights can help build trust, reinforce existing collaboration among S3 stakeholders (Kleibrink et al., 2016), and offer an enhanced understanding of regional knowledge stocks (Magro and Wilson, 2013), which can translate into innovative knowledge recombination processes (Melero and Palomeras, 2015). Therefore, our methodology can contribute to the development of S3 monitoring systems (Tolias, 2019), which can act as 'early-warning mechanisms' (Gianelle et al., 2019) for detecting faulty decision making and providing direction for continuous improvement.

No relevant issues serving to raise questions as to the value of the proposed methodology have been detected while conducting the pilot experiment. In addition, it is important to note that the methodology, to some extent, can be personalised. In our pilot, for example, the USPTO database was preferred due to its granularity and the richness of data available. Nonetheless, further applications of our study may rely on different databases, such as Espacenet or REGPAT (OECD, 2020). In addition, the time frame for the analysis, as well as the regions and their S3 priorities to be examined, can easily be changed to fit emerging research needs.

Finally, three noteworthy limitations have surfaced while conducting the study, which did not undermine the proposed methodology but opened interesting opportunities for future research. The first limitation arose whilst attempting to align the IPC technological classes with the S3 priorities encoded in the Eye@RIS3 tool that the regions under investigation have included in their smart specialisation strategies. Matching IPC classes and S3 priorities has proven effective in the framework of our pilot study, but it might be particularly laborious when the activity is conducted for large-scale analyses since this activity is heavily reliant on the selection proposed by patent experts and the use of existing patent classifications. Integrating computer-assisted techniques, such as text mining, can automatise this activity, thereby increasing reliability and consistency while reducing the investment of time and effort.

The second limitation relates to a widely acknowledged challenge for anyone involved in patent analyses: not all inventions are patented (Zuniga et al., 2009). For instance, depending on the nature of the invention and the business of its inventor, some intellectual products are protected as trade secrets rather than being patented, to avoid public disclosure. Some common examples include innovative formulas, practices, designs, and manufacturing processes. As a result, the proposed patent-based analysis of regional technological capabilities may lead to imperfect results, due to possible missing information. Considering that measures based on patent data are currently the most suitable source of knowledge for discovering regional patterns of technological evolution (Ardito et al., 2018; Lee and Lee, 2013), these possible imprecisions should not discourage the deployment of the proposed methodology, because they can be mitigated by adopting a multi-method approach to data-driven decision making, in which complementary evidence is combined, rather than relying on a single source.

Moreover, by using the approach proposed by Hall et al. (2001), we avoided potential correlation effects among the proposed indicators, due to sectorial composition and time. Nonetheless, future studies may collect a higher number of observations to test for the presence of underlying unobserved factors that may partially affect the results of the analysis, in order to further increase the robustness of the proposed methodology.

The methodological contribution offered by this paper should not be interpreted as a stand-alone application. For instance, further research may complement our methodology with indicators aiming at capturing opportunities of inter-regional collaborations, in order to make S3 more effective. In addition, the proposed methodology may also be deemed as complimentary to the tools and techniques for regional context analysis that are already available. The Online S3 Platform, for example, offers seven digital applications to inform S3 design. These applications can easily produce additional technology-related contextual information which represents a supplement to the knowledge base developed by our methodology, such as: the presence of research infrastructures, innovation clusters, and incubators across EU regions; regional scientific production profiles based on bibliometric data; and regional technological trends uncovered by looking into grant data.

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