



Territorial Patterns of European Innovation in the Context of Different Innovation Output Proxies: A Spatial MGWR-SAR Approach

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Abstract

The paper seeks to explore the drivers of European innovation represented by three innovation outputs (patent, trademark, and design applications), emphasizing spatial autocorrelation and heterogeneity. It includes data from 202 regions from 22 European Union (EU) Member States, along with 18 regions from Switzerland, Norway, and Serbia in 2019, providing a more comprehensive geographic scope. By considering multiple indicators of innovation output, including patents, trademarks, and design applications, the main objective is to examine spatial innovation spillovers and the heterogeneous responses of regional innovation output to innovation inputs in the context of European regions. To achieve this goal, the main instrument of the analysis is a newly proposed methodological framework called Mixed Geographically Weighted Regression-Spatial Autoregressive (MGWR-SAR) models. The analysis suggests that while all innovation inputs (most-cited publications, research and development expenditure in the business sector, human resources in science and technology, and population density) are justified in increasing all innovation outputs, the strength of particular determinants of innovation might vary across regions. Moreover, the analysis reveals valuable insights into how spatial spillovers influence regional innovation. The impact of spatial connections varies across the regions, with patents showing the strongest linkages, affecting about 92.27% of regions. Although trademarks and designs have fewer spatial connections (approximately 50% of regions), they still play a significant role in innovation. Although patents have traditionally dominated discussions of innovation, the findings reveal the importance of incorporating designs and trademarks as complementary indicators. Overall, the study highlights the need for multiple metrics to comprehensively evaluate innovations.

Keywords Spatial autocorrelation · Spatial heterogeneity · Mixed geographically weighted regression–spatial autoregressive model · Innovation outputs

JEL Classification O31 · R12

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Introduction

Nowadays, most research and development (R&D) policies, as well as economic development theories, perceive research and innovation as key success factors determining employment and economic growth. Increased R&D investment leads to the development of technologically innovative products, enabling companies to gain benefits such as increased market share, ultimately contributing to economic growth and employment (Kinkel et al., 2005). While these conclusions emerge from numerous empirical studies, many issues related to the innovation process remain unclear. Problems such as the origin of innovation, the primary drivers of innovation, and the impact of location on innovation persist. It is evident that innovation is driven by internal factors within firms (e.g., capabilities, processes, or human resources), but the influence of external factors and spatial aspects is increasingly highlighted. The external environment can stimulate innovation through connections between research centers, industries, or higher education institutions. For instance, in the study by Guastella and Van Oort (2015), localized spillovers of knowledge were considered to explain the spatial concentration of innovation activities.

According to Radošević et al. (2017), there is a need to focus more on regionally specific strategies, especially in the catch-up regions of the European Union (EU), where innovation often relies on the gradual improvement and adoption of existing technologies rather than large investments in research and development. Universities in these areas should prioritize increasing knowledge dissemination capacities to facilitate the dissemination of expertise from key regions and inform local firms of available technologies. In addition, policies should prioritize the promotion of cooperation between leading research universities in core regions and universities in catch-up regions, possibly through funding schemes to stimulate cooperation and the establishment of regional universities in catch-up regions to strengthen knowledge transfer capabilities.

Given these considerations, the evaluation of innovation performance at the regional level has become imperative. However, the scarcity of regional innovation data poses challenges, complicating comparative assessments of regional innovation systems and measurements of innovation. A valuable data source for addressing these challenges in the context of examining the innovation activities of European regions is the Regional Innovation Scoreboard (RIS), which provides statistical information on the innovation performance of regions. The RIS 2019 report (Hollanders et al., 2019) offers an evaluation of innovation systems performance across EU Member States regions, Serbia, Norway, and Switzerland. The Oslo Manual (OECD/Eurostat, 2018) serves as another valuable data source for understanding and measuring innovation within firms and across industries. Developed by the Organization for Economic Cooperation and Development (OECD), it offers standardized guidelines and methodologies for collecting and interpreting innovation data. Through internationally agreed-upon definitions and practices, the manual ensures consistency in measuring innovation activities such as R&D, technology adoption, and organizational changes. Utilizing the Oslo Manual as a data source

enables countries and organizations to gather reliable and comparable information on innovation performance.

In contemporary research on regional innovation activities, the conventional reliance on patents as the primary proxy for measuring innovation outputs has been challenged. In this paper, we try to propose a novel approach to regional innovation evaluation by expanding the scope of innovation output proxies to include trademark applications and design applications. By considering multiple indicators of innovation output, including patents, trademarks, and design applications, our main objective is to examine spatial innovation spillovers and the heterogeneous responses of regional innovation output to innovation inputs in the context of European regions. To address this goal, we employ a methodological framework that integrates Mixed Geographically Weighted Regression-Spatial Autoregressive (MGWR-SAR) models. This approach enables us to simultaneously examine spatial autocorrelation and heterogeneity while considering multiple innovation output proxies. Given the outlined goal and research methodology, this paper aims to answer the following research questions:

- **Innovation Output Proxies:** We hypothesize that the inclusion of trademark and design applications alongside patents as proxies for innovation output will provide a more comprehensive understanding of regional innovation dynamics compared to using patents alone.
- **Spatial Innovation Spillovers among European regions:** We hypothesize that regional innovation spillovers might lead to increased innovation activities in neighboring regions (indicated by patents, trademarks, and designs).
- **Spatial Differentiation of Model Parameters:** We hypothesize that the parameters of MGWR-SAR models will demonstrate spatial differentiation, indicating varying levels of spatial dependence and innovation drivers across different regions of Europe.
- **Spatial Autocorrelation and Heterogeneity¹:** We assume that spatial autocorrelation and heterogeneity will coexist in the regional innovation environment, reflecting both spatial innovation spillovers and variations in innovation patterns across regions, with model parameters expected to vary over space.

By applying the MGWR-SAR models to regional innovation data encompassing patents, trademarks, and design applications, our aim is to provide a comprehensive

¹ Spatial autocorrelation refers to the positive or negative correlation of a variable with itself due to the spatial location of observations. It can result from complex, unobservable processes such as interaction phenomena or technological diffusion. On the other hand, spatial heterogeneity acknowledges that the influence of explanatory variables on the dependent variable varies across observation locations. In the context of the regional innovation problem, spatial autocorrelation refers to the positive or negative correlation of innovation activities within a region with those in neighboring regions. This means that regions with high levels of innovation tend to be spatially clustered, while regions with low levels of innovation are also clustered together. Spatial heterogeneity, on the other hand, refers to the variation in the strength and nature of innovation processes across different regions. This implies that the factors influencing innovation outcomes, such as access to resources, infrastructure, or human capital, may vary from one region to another.

analysis of the regional innovation environment, particularly focusing on the European regions. These findings may have significant implications for regional innovation policy. If the spatial non-stationarity of the parameters were confirmed, regional policy instruments would have to be heterogeneous. In addition, differences may arise in relation to different innovation outputs. Our use of MGWR-SAR models serves as a primary validation tool to address these research questions. To the best of the author's knowledge, this is the first analysis of the regional innovation problem considering both spatial effects based on the MGWR-SAR approach, with the three innovation outputs being modeled variables.² Simultaneous examination of both spatial effects is rarely conducted, not only in relation to innovation activities of the regions. One reason for this may be the scarcity of spatial econometric tools suitable for addressing both problems simultaneously. It appears that one of the few possibilities is a new class of MGWR-SAR models (Geniaux & Martinetti, 2018).

The rest of the paper is structured as follows: the next section provides a literature overview; the Methodology section includes data and study area descriptions and the main theoretical backgrounds of the study. Empirical results are presented and interpreted in the Results and Discussion section. The main concluding remarks can be found in the Conclusion and Limitations and Future Research section. The paper closes with references. Additional tables and figures are included in the Annex.

Literature Review

One of the key questions when measuring innovation is the question of what can be considered an innovation output. Economists (e.g., Griliches, 1990 or Jaffe & de Rassenfossé, 2017) have been debating about the issues of measuring innovative activity and technological progress but the answer is not so straightforward and innovation output can be represented in various ways. The term “inputs to innovation” generally refers to the resources committed to innovation (investment in R&D and intellectual capital) and the term “innovation output” refers to the new products and processes announcements. The capacity of firms to develop new products determines their competitive advantage. For this reason, the number of patents is considered the main indicator of the rate of new product innovation. Patents, while valuable for protecting technical innovations, have limitations in capturing certain types of innovation comprehensively. This includes non-technical innovations and those that may not meet patentability criteria. Additionally, the time-consuming and costly nature of obtaining patents, coupled with the requirement for detailed disclosure, may render them less suitable for some businesses. In such cases, designs or trademarks offer alternative forms of intellectual property protection. Designs might be ideal for safeguarding the aesthetic aspects of products, while trademarks excel in protecting brand identity and market presence. These options are often simpler and more cost-effective to obtain, providing valuable protection for a broader range of

² The author has already published papers (Furková, 2021 and Furková, 2022) where the MGWR-SAR approach has been applied but only in connection with patents as an innovation output.

innovations and intellectual property assets. Patent applications tend to be lower at service companies than in the manufacturing sector; trademarks and design applications are a privileged method of registration in the services segment (Blind et al., 2003). Trademarks and designs as well as patent applications constitute property rights but of a different nature and they are considered important innovation indicators. The Oslo Manual (OECD/Eurostat, 2018) also outlines different indicators and methods to capture different aspects of innovation, such as R&D expenditure, patents, trademarks, and design registrations.

The relationship between the inputs and outputs provides information on the R&D effectiveness. The well-known concept of the Regional Knowledge Production Function (RKPF) model (see Pakes & Griliches, 1980 or Moreno et al., 2005a) is one of the options to model the relationship between the innovation inputs and outputs. In Jaffe (1989), the RKPF model extension to spatial context was introduced. Jaffe also noted that when discussing data on the inputs, outputs, and effectiveness of innovative activity, it is important to distinguish between the underlying concept of concern and the proxy or measure used to indicate innovation. In many empirical studies (e.g., Autant-Bernard & LeSage, 2011; Charlot et al., 2015; Moreno et al., 2005a, 2005b; Popescu et al., 2023), the number of patent applications has been accepted as innovation output.

Table 10 (see Annex) provides a more comprehensive overview of papers focused mostly on patent applications as an innovation output. The number of patent applications is also an inevitable part of the RIS innovation indicators.

In empirical analyses that examine the innovative activities of companies or regions, designs and trademarks are mentioned much less compared to patents. Mendonça et al. (2004) took the first important step in analyzing trademarks as an innovation indicator, which they define as a partial or complementary measure of innovative output for firms. The authors suggest that trademarks must be combined with additional data to produce consistent results regarding innovation. Their analysis confirms the close relationship between innovation and the marketing efforts of companies. Additionally, trademarks often accompany the introduction of new and innovative products and services to the market, expressing the innovativeness of these products or services. Gotsch and Hipp (2012) assessed the use of trademarks as innovation indicators, particularly for services where traditional metrics fall short. Their study, based on European Community Innovation Survey data, showed a positive correlation between trademark registration and innovation success among German firms. They also noted that knowledge-intensive business services tend to favor trademarks over patents for safeguarding innovation. Similarly, Flikkema et al. (2014) conducted a study on small- and medium-sized enterprises in the Benelux countries. They found that nearly 60% of registered trademarks were linked to innovation activities, primarily the launch of new products or services. Their findings support the notion of trademarks as effective innovation indicators for SMEs.

The research in Ribeiro et al. (2022) also emphasizes the value of trademark data as complementary indicators of innovation alongside patents. It presents evidence from extensive trademark and patent databases, showing a strong correlation between the two across various scales. By incorporating trademark data, the study suggests a more comprehensive understanding of innovation processes, especially

in-service sectors, low-patent-usage sectors, and among exporting entities in developing countries. Overall, it underlines the importance of integrating trademark data into innovation studies to capture diverse forms of innovation effectively.

As outlined in previous empirical research (e.g., Audretsch & Feldman, 2004; Kumar, 2008; Charlot et al., 2015; Guastella van Oort, 2015; Kijek & Kijek, 2019; Furková, 2021, 2022), spatial interconnections and geographical proximity across European regions may significantly affect spatial patterns of innovation. In this context, not only regional capacities are relevant in determining local innovation. For instance, this means that the knowledge produced in a region may disperse to neighboring regions, which might influence innovation actions in these regions. In addition, a geographical closeness affords the opportunity for knowledge to spread faster. Therefore, the role of so-called spatial spillovers should not be neglected in determining regional innovation.

A study by Lilles et al. (2020) points out that in the catching-up regions of the EU, innovation is primarily incremental, relying on existing technologies rather than significant R&D investment. Universities in these areas should enhance knowledge translation to spread expertise from core regions to local firms. Moreover, fostering collaboration between leading research universities in core regions and those in catching-up regions can boost knowledge transfer networks and establish regional universities for stronger innovation capabilities. In Table 10 (see Annex), we present a list of papers and the main findings of research studies focusing on European regional knowledge production processes with spatial spillovers, employing mainly patents as the primary indicator of innovation output.

In this research, we consider the possibility that spatial autocorrelation might be present simultaneously with spatial heterogeneity. We suppose non-uniform distribution of European innovation that is a spatial heterogeneity problem. At the same time, spatial innovation spillovers are considered an external determinant of regional innovation (spatial autocorrelation problem). Simultaneous examination of both spatial effects is rarely examined, not only in relation to innovation activities of the regions. One of the reasons for this may be the fact that tools of spatial econometric suitable for solving both problems at the same time are very sparse. It seems that one of the few possibilities is a new class of MGWR-SAR models (Geniaux & Martinetti, 2018). Another two innovative approaches for addressing spatial autocorrelation and heterogeneity simultaneously in spatial data analysis can be found in the work of Chen et al. (2022) and Wu et al. (2023). Chen et al. (2022) proposed a backfitting method for the geographically weighted regression model with a spatially autoregressive term (GWR-LAG) model to address spatial autocorrelation and heterogeneity simultaneously. This approach enables optimal bandwidth selection for each coefficient, improving estimator accuracy and enhancing model performance. In contrast, Wu et al. (2023) introduced unified geographically weighted regression (UGWR) models, allowing regression coefficients to vary across space and considering spatial autoregressive relationships. Their reconstruction parameterization approach offers flexibility in fitting different smoothness degrees, demonstrating superior performance in handling complex datasets through simulation and empirical studies, notably on China's regional GDP dataset. Both approaches offer significant advances in understanding spatial phenomena.

Methodology

This section provides an overview of the study area and data, the spatial differentiation of innovation outputs, and the main methodological background.

Data and Study Area

European regions play an active role in regional development, in shaping innovation trajectories (Żóltaszek & Olejnik, 2021), and they are targeted by regional policies. In addition to national and the EU-level policies, innovation policy in Europe is increasingly being designed and implemented at a regional level. The regions that are lagging behind can apply for EU funding support. For example, EU regions are the focus of cohesion policy (see, e.g., Hahn & Andor, 2013), which provides territories special care and investment tools to address specific issues. The components of the Regional Innovation Index (RII)³ obtained from the Regional Innovation Scoreboard (RIS) 2019 (Hollanders et al., 2019) and the Eurostat regional statistical database (Eurostat, 2022) are used as data sources for the empirical analysis. The RIS is an initiative of the European Commission (Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs) that provides a comparative assessment of the innovation performance of regions in Europe and some countries outside Europe. The Scoreboard aims to help policymakers, stakeholders, and researchers understand and assess the innovation environment at the regional level.

The RIS covers 238 regions in 23 EU Member States, Norway, Serbia, and Switzerland at different NUTS (Nomenclature of territorial units for statistics) levels. The NUTS classification is a hierarchical system for dividing the economic territory of the EU, which distinguishes between three levels: NUTS 1 captures major socio-economic regions, NUTS 2 captures basic regions for the application of regional policies, and NUTS 3 captures small regions for specific diagnoses (Hollanders et al., 2019).

The analysis considers classification mainly according to NUTS 2 level.⁴ This level of classification is deemed appropriate for the analysis because regions eligible for cohesion policy support are defined at the NUTS 2 level. This NUTS classification is chosen in most research works dealing with the examination of innovation processes across European regions (e.g., Popescu et al., 2023; Halásková & Bednář, 2023; Bristow & Healy, 2018 or Charlot et al., 2015). The research in Kijek and Kijek (2019) also uses data for NUTS 2 EU regions. The authors argue that spatial models for these regions make it possible to study the role of knowledge and human capital spillovers dispersed through various proximate linkages. More studies are listed in Table 10 in the Annex.

³ According to RIS 2019, regional innovation performance is measured using a composite indicator – the Regional Innovation Index (RII) which summarizes the performance on 17 indicators (see Hollanders et al., 2019).

⁴ Depending on differences in regional data availability, the RIS covers 32 NUTS 1 level regions and for this reason, 30 regions at this level are included in our analysis.

The analysis in this paper encompasses 202 regions of 22 EU Member States⁵ along with 18 regions from Switzerland, Norway, and Serbia, providing a more comprehensive geographic scope that spans both EU and non-EU countries within Europe. We assume that these non-EU regions are appropriate to add to the dataset because they are direct geographical neighbors of EU regions. This coverage is instrumental in examining spatial connectivity in the context of innovation, facilitating the exploration of cross-regional collaboration and initiatives aimed at fostering interconnectedness among regions across diverse geopolitical borders. To address issues such as isolated observations (island regions) and missing data, corresponding regions were removed from the analysis. The resulting study area is shown in Figs. 1, 2, and 3.⁶

As stated in the introduction of this paper, in addition to patents as one of the most commonly used innovation output proxy, we also turn our attention to other potential proxies of innovation output. Trademark and design applications are also considered proxies for innovation output of the regions. The rationale for this choice is given in a short discussion in the Introduction and Literature Review sections. Tables 1, 2 and 3 also provide a brief overview of the adequacy of these indicators as representatives of innovation outputs. The tables also contain a detailed description of these variables along with their basic descriptive statistics. The data refer to the year 2019.

Figures 1, 2 and 3 illustrate the real and simulated spatial distributions of PCT applications, trademark applications, and design application, respectively. All three indicators are part of the RII index and will be modelled variables of the next econometric analysis.

Geographical differences in performance for PCT applications can be observed from Fig. 1 (see the left side). Most of the Eastern European regions, the regions of Spain, Greece, and southern Italy, achieve relatively low values of patents. On the other hand, the regions of Germany, Finland, Sweden, Switzerland, the Netherlands, or Denmark are mainly the top performers. The score value of 1 (the highest possible) reached the Dutch region Noord-Brabant, Swedish region Sydsverige and German region Oberpfalz. The region Noord-Brabant has a high share of high-tech companies, the region Sydsverige is characterized by a diversified business environment, with several established clusters and several strong universities which are very beneficial as well. The region Oberpfalz is a component of a strong Bavarian regional innovation system which strength stems from the numerous innovation networks and clusters (Furková, 2022).

To summarize the top performing regions, we present the top ten performing regions for each innovation output in Table 11 (see Annex). We can note that for each innovative output, the first place belongs to three regions with the same value of the indicator. The table also contains the affiliation of the region to the country as well as the NUTS code.

⁵ The UK was still part of the EU during the period under observation, and is therefore included in the set of regions of the EU member states.

⁶ All figures and tables in this paper are elaborated by the author on the basis of RIS 2019 data (Hollanders et al., 2019) and data from the regional Eurostat statistics database (<http://ec.europa.eu/eurostat/>). All calculations as well as maps were implemented with RStudio and GeoDa software.

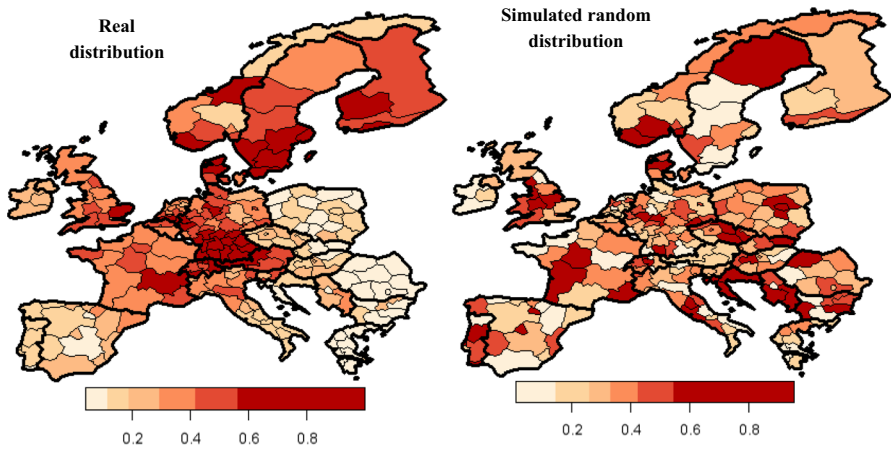


Fig. 1 Comparison of differences between real (left) and simulated random distribution (right) for patent applications

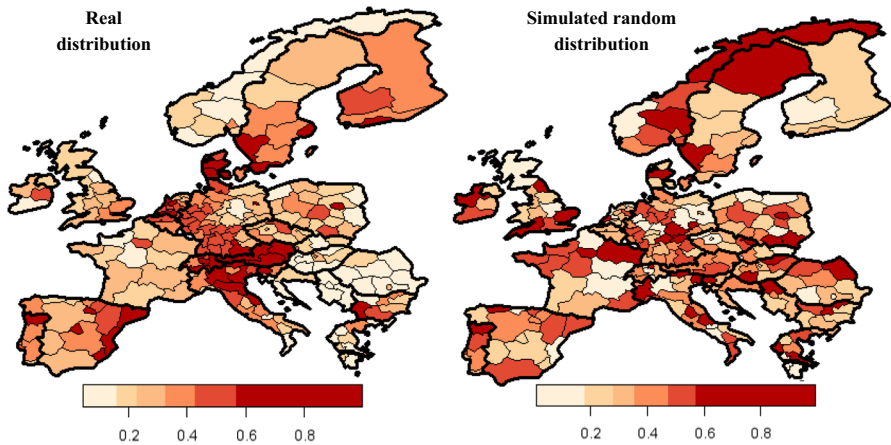


Fig. 2 Comparison of differences between real (left) and simulated random distribution (right) for trademark applications

Performance on trademark applications shown in Fig. 2 (left side) is relatively strong in Austria, Denmark, and Switzerland. Other countries with high-performing regions include, e.g., Belgium, Spain, Germany, Sweden, and Italy. The highest possible score was achieved by the Spanish region of La Rioja and two Swiss regions Zentralschweiz and Ticino (see Table 11 in Annex). The leadership of the Swiss regions is certainly supported by innovation parks which facilitate collaborations for companies, start-ups, and universities to find solutions to some of the world's most pressing challenges (see <https://www.switzerland-innovation.com/>). Such an innovation network enables accelerating the transformation of research results into marketable products and services. The third leading region in relation to trademarks, the

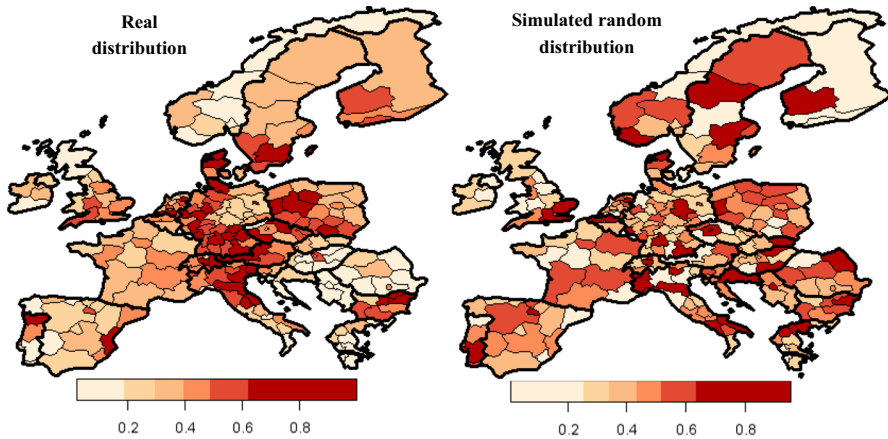


Fig. 3 Comparison of differences between real (left) and simulated random distribution (right) for design applications

Spanish region of La Rioja, has a significant industrial base focused on the agri-food sector. In recent years, the wine sector has focused on quality and innovation, with the Rioja Qualified Designation of Origin becoming one of the internationally recognized wine designations (see <https://what-europe-does-for-me.eu/en/portal/1/ES23-ES230>). It is the identification of the origin of goods and services that is one of the essential functions of a trademark. Compared to PCT applications, trademark applications are characterized by higher differences in regional performance within countries. Large differences are observed for instance in Spain or Bulgaria.

Finally, Fig. 3 (left side) shows the geographical performance differences in design applications. High-performing regions are mostly the regions of Austria, Czech Republic, Germany, Denmark, the Netherlands, Italy, and Poland. Countries such as Greece,

Table 1 Innovation output—PCT applications

PCT applications

Category: Dependent variable MGWR–SAR1 model

Definition: Patent Cooperation Treaty (PCT) applications at the European Patent Office (EPO) per billion regional gross domestic product (GDP)

Numerator: Number of patents applied for at the EPO, by year of filing. The regional distribution of the patent applications is assigned according to the address of the inventor

Denominator: Gross Domestic Product in Purchasing Power Standard

Rationale (Hollanders et al., 2019): The capacity of firms to develop new products determines their competitive advantage. One indicator of the rate of new product innovation is the number of patents.

This indicator measures the number of patent applications at the European Patent Office

Form: Normalized^a

Source: Regional Innovation Scoreboard 2019

Basic descriptive statistics:

Min	First Quartile	Median	Mean	Third Quartile	Max	Stand. dev
0.039	0.136	0.291	0.336	0.474	1.000	0.229

^aThe RIS 2019 provides data which are already normalised by the min–max procedure (data range from 0 to 1)

Table 2 Innovation output—trademark applications

Trademark applications

Category: Dependent variable MGWR–SAR2 model

Definition: Trademark applications at European Union Intellectual Property Office (EUIPO) per billion regional Gross Domestic Product (GDP)

Numerator: Number of trademarks applied for at EUIPO

Denominator: Gross Domestic Product in Purchasing Power Standard

Rationale (Hollanders et al., 2019): Trademarks are an important innovation indicator, especially for the service sector. The Community trademark gives its proprietor a uniform right applicable in all Member States of the European Union through a single procedure which simplifies trademark policies at European level. It fulfils the three essential functions of a trademark: it identifies the origin of goods and services, guarantees consistent quality through evidence of the company's commitment vis-a-vis the consumer, and is a form of communication, a basis for publicity and advertising

Form: Normalized^a

Source: Regional Innovation Scoreboard 2019

Basic descriptive statistics:

Min	First Quartile	Median	Mean	Third Quartile	Max	Stand. dev
0.043	0.184	0.323	0.362	0.493	1.000	0.216

^aThe RIS 2019 provides data which are already normalised by the min–max procedure (data range from 0 to 1)

Croatia, Norway, Lithuania, Romania, and Slovakia have high proportions of low-performing regions. The Italian region of Umbria, the Czech region of Jihozapad, and the Swiss region of Ostschweiz are the best performing regions (see Table 11 in Annex). Let us take a closer look into the Czech region of Jihozapad. This region is one of the few

Table 3 Innovation output—design applications

Design applications

Category: Dependent variable MGWR–SAR3 model

Definition: Design applications at European Union Intellectual Property Office (EUIPO) per billion regional Gross Domestic Product (GDP)

Numerator: Number of designs applied for at EUIPO

Denominator: Gross Domestic Product in Purchasing Power Standard

Rationale (Hollanders et al., 2019): A design is the outward appearance of a product or part of it resulting from the lines, contours, colors, shape, texture, materials, and/or its ornamentation. A product can be any industrial or handicraft item including packaging, graphic symbols, and typographic typefaces but excluding computer programs. It also includes products that are composed of multiple components, which may be disassembled and reassembled. Community design protection is directly enforceable in each Member State and it provides both the option of an unregistered and a registered Community design right for one area encompassing all Member States

Form: Normalized^a

Source: Regional Innovation Scoreboard 2019

Basic descriptive statistics:

Min	First Quartile	Median	Mean	Third Quartile	Max	Stand. dev
0.024	0.248	0.392	0.405	0.552	1.000	0.215

^aThe RIS 2019 provides data which are already normalised by the min–max procedure (data range from 0 to 1)

exceptions when a region from the former Eastern bloc and, in addition, a region that is included in the group of less developed regions (regional gross domestic product (GDP) less than 75% of the EU average) ranks first in connection with any component of the RII index. The Jihozápad region has a tradition in light (automotive) engineering, food and beverage manufacturing, and agriculture. Clusters in the manufacturing branches can potentially be an explanatory factor for the good performance of the industries in Jihozápad and potential for the development of innovation clusters in this region, with an impact on regional smart specialization. In addition, within the Czech Republic, Jihozápad certainly profits from its geographic location and proximity of business partners in Bavaria and Austria in respect of business collaboration and the attraction of investments in the region. The cluster additionally can draw innovative potential from co-operation with the nearby academic institution (University of West Bohemia), which offers electrical engineering, mechanical engineering, and applied sciences programs (Cordes et al., 2016). In comparison to patent protection (used to protect the way a product works), a registered design protects the appearance of a product which may consist of its lines, contours, shape, colors patterns, etc. Design protection plays an essential role in the automotive or food industry that are major industries in Jihozápad region.

Together, for all three considered innovation outputs, we can conclude that the common feature of the top-performing regions is the geographical concentration of clusters of innovative firms and research hubs, which enable them to draw from technological development and share experiences with knowledge, technologies, etc. It is clear that, in terms of all three innovation outputs, innovation activities in the European area are unevenly distributed and innovation is likely to be spatially correlated. Figures 1, 2 and 3 illustrate the gap between real—probably spatially autocorrelated distribution (on the left)—and simulated random distribution (on the right) for patent, trademark, and design applications.

The well-known Moran's I test⁷ can be used as an initial inspection of spatial autocorrelation. The global Moran indexes presented in Table 4 show strong evidence of spatial association for the values of real distributions. This indicates that the values of patents, trademarks, and designs are not randomly distributed in space but there is a particular relationship between corresponding innovation output and its spatial lag. On the contrary, the observations have no special spatial patterns in case of simulated random distributions.

The discussion and calculations above (see Table 4) suggest that the location of the region and the nature of the neighborhood occupy a significant position for the generation of regional innovation in terms of all three considered innovation outputs. Therefore, considering spatial autocorrelation and heterogeneity at the same time seems essential.

To simultaneously address both spatial effects in spatial econometric models, we will utilize the extended RKPF model and the MGWR-SAR approach presented in the following section. Table 5 provides a description of all explanatory variables (innovation inputs) used in the econometric analysis.

The explanatory variables, “Top 10% most-cited publications” and “R&D expenditures in the business sector,” used in the following analysis, are significant

⁷ Spatial weighting queen contiguity scheme (for more details, see, e.g., Anselin & Rey, 2014 or section Econometric Models) was applied for Moran's I calculations.

Table 4 Moran's Index of PCT applications, trademark applications, and design applications

	PCT applications		Trademark applications		Design applications	
	Real distribution	Simulated random distribution	Real distribution	Simulated random distribution	Real distribution	Simulated random distribution
Moran's Index	0.6731***	0.0539	0.4280***	-0.0752*	0.4110***	0.0211
Pseudo <i>p</i> -value	0.0010	0.1190	0.0010	0.0780	0.0010	0.2760

Symbols *** and * indicate statistical significance at 1% and 10% level of significance

Table 5 Explanatory variables descriptions

Category	Definition	Form
Explanatory variables (all models):		
Top 10% most-cited publications	Scientific publications among the top 10% most cited publications worldwide as percentage of total scientific publications	Normalized ^a
R&D expenditure in the business sector	R&D expenditures in the business sector as percentage of regional GDP	Normalized ^a
Human resources in science and technology (HRST ^a)	HRST as percentage of the active population	Normalized ^a
Population density ^b	Persons per square kilometer	Normalized ^c
Lagging regions (DUM_{LAGG})	The regions whose GDP per capita is less than 75% of the average GDP of the EU-27. $DUM_{LAGG} = 1$, if region belongs to the category of lagging regions, others = 0	Dummy variable
Lagging regions (DUM_{LAGG}) × human resources in science and technology	The interactive dummy variable DUM_{LAGG} with HRST variable	Interactive dummy variable

^aThe RIS 2019 provides data which are already normalised by the min-max procedure (data range from 0 to 1)

^bThe ratio between the annual average population and the land area of the region

^cThe min-max procedure was applied

elements of the RII index, which was one of the main reasons for their inclusion. A rationale for why these variables should be included as potentially significant innovation inputs is provided in Hollanders et al. (2019). The variables “Human resources in science and technology” and “Population density” were obtained from the regional Eurostat statistics database (Eurostat, 2022). The data refer to 2019, except for the variable “Population density”; we used data for 2018 due to data availability. In order to control for additional regional characteristics, two dummy variables for lagging (less developed) regions are considered. The classification of less developed or lagging regions in our study adheres to the categories outlined in the EU Cohesion Policy, as described by, e.g., Hahn and Andor (2013). According to this classification, less developed or lagging regions are those whose GDP per capita is less than 75% of the average GDP of the EU-27. In this context, a dummy variable representing a lagging region takes the value of 1 if the observation is a lagging region and 0 otherwise. On the other hand, an interactive form with a variable representing human resources in science and technology allows for the exploration of how the effect of lagging region on innovation output changes based on the level of human resources in science and technology.

Econometric Models

In this paper, we employ a new model to accommodate spatial autocorrelation and heterogeneity simultaneously. Applying such an approach seems reasonable for two reasons. Firstly, innovation of a region can be affected by innovation actions carried out in surrounding regions (see, e.g., Moreno et al., 2005a; Furková, 2021); thus, the problem of spatial autocorrelation may be present. In addition, it can be also expected that the strength of individual determinants of innovation might vary across European regions. Therefore, the spatial heterogeneity problem should be considered. Both of these issues are addressed through the MGWR-SAR model but neglected in the traditional ordinary least squares (OLS) concept. Nevertheless, the starting point of our analysis for identifying regional innovation determinants is OLS regression. The OLS model can be written as:

$$y_i = \mathbf{X}_i\boldsymbol{\beta} + \varepsilon_i, \quad \forall i \in \{1, \dots, N\}, \quad (1)$$

where \mathbf{y} is the N -vector of a dependent variable (N is a size of the sample); \mathbf{X} is a matrix of k exogenous explanatory variables (k is a number of explanatory variables); $\boldsymbol{\beta}$ is a k vector of unknown parameters and ε is an IID (independent and identically distributed) error term representing all unobservable factors that influence regional innovative performance. Based on the OLS estimate and the resulting *LM* tests (see, e.g., Anselin & Rey, 2014), the type of spatial econometric model can be determined. In spatial econometric literature, a regression model that explicitly considers spatial autocorrelation of the endogenous variable y is denoted as SAR (spatial autoregressive) model. This model incorporates a spatial lag term $\mathbf{W}\mathbf{y}$ that captures the influence of neighboring observations on the dependent variable. This model is formally written as follows:

$$y_i = \rho\mathbf{W}\mathbf{y} + \mathbf{X}_i\boldsymbol{\beta} + \varepsilon_i, \quad \forall i \in \{1, \dots, N\}, \quad (2)$$

where ρ denotes a parameter of spatial autoregressive process, $\mathbf{W}\mathbf{y}$ is a spatially lagged dependent variable, and $W = (w_{ij} : i, j = 1, \dots, N)$ represents a spatial weighting matrix, which summarizes the spatial relationships between N regions. The estimation of all spatial econometric models in this paper is based on queen contiguity weights. These weights indicate whether regions share a boundary or not. Corresponding spatial weights are taking two values: 1—when there is a common border between two regions; 0—otherwise. This spatial weighting scheme—row-standardized queen contiguity form—is applied in all empirical estimations as well as spatial statistics calculations in this paper.

In model (2), the parameter ρ and the linear regression parameters β are constant for all locations. This idea is adopted by all existing estimators of SAR, which seems to be a restrictive assumption. In addition, Geniaux and Martinetti (2018) remind us that it is often a problem to distinguish real spatial autocorrelation and various sources of violation of IID, such as spatial heterogeneity through unobserved covariates and/or spatially varying relationships. The term spatial heterogeneity is associated to structural instability and heteroscedasticity. The structural instability relates to the spatial non-stationarity of the parameters and heteroscedasticity covers the problem of different error variances of the spatial units. Given the regional innovation problem in a territory as large as the European area, it can be assumed that the strength of the impact of innovation determinants may differ from region to region.

In order to improve SAR estimates and allow for simultaneous consideration of spatial autocorrelation as well as spatially varying parameters (spatial heterogeneity), Geniaux and Martinetti (2018) propose a new class of data generating process (DGP) known as MGWR-SAR models. They suggest that values of parameters ρ and β s depend on the coordinates (u_i, v_i) representing the longitude and latitude of observation i . The model that considers the existence of global and local variables (including the spatial autoregressive parameter) takes the following form:

$$y_i = \rho(u_i, v_i; h) \mathbf{W}\mathbf{y} + \beta_C X_C + \beta_V(u_i, v_i; h) X_V + \varepsilon_i \forall i \in \{1, \dots, N\}, \quad (3)$$

where h is a bandwidth parameter that enables us to determine a local subsample around the coordinates of each region (u_i, v_i) using a given distance kernel function, k_C is the number of constant β s, k_V is the number of spatially varying β s, X_C represents k_C explanatory variables with constant parameters (β_C), and X_V represents k_V explanatory variables with spatially varying parameters (β_V).

The MGWR-SAR models are developed based on the combination SAR model (model defined in (2)), geographically weighted regression (GWR) (Brunsdon et al., 1996), and mixed geographically weighted regression (MGWR) (Fotheringham et al., 1999; Geniaux et al., 2011; Mei et al., 2004) models. GWR and MGWR are spatial regression techniques that allow model parameters to vary spatially, capturing local variations in relationships between variables (spatial heterogeneity problem). The integration of MGWR-SAR models combines the strengths of GWR, MGWR, and SAR approaches. It allows for the simultaneous consideration of spatial heterogeneity (through GWR or MGWR) and spatial autocorrelation (through SAR). This integration enables researchers to capture both local variations in relationships and spatial dependencies among observations. MGWR-SAR models are

particularly well-suited for analyzing spatially complex datasets where relationships between variables may vary across different geographic regions. From Eq. (3), we can derive nine different DGPs (Geniaux & Martinetti, 2018) as a combination of fixed and spatially-varying coefficients (ρ, β_C, β_V):

$$\begin{aligned}
 y_i &= \beta_C X_C && + \varepsilon_i && \text{(OLS)} \\
 y_i &= \beta_V(u_i, v_i; h) X_V && + \varepsilon_i && \text{(GWR)} \\
 y_i &= \beta_C X_C + \beta_V(u_i, v_i; h) X_V && + \varepsilon_i && \text{(MGWR)} \\
 y_i &= \rho W y + \beta_C X_C && + \varepsilon_i && \text{(SAR)} \\
 y_i &= \rho W y + \beta_V(u_i, v_i; h) X_V && + \varepsilon_i && \text{(MGWR-SAR}(0,0, k)) \\
 y_i &= \rho W y + \beta_C X_C + \beta_V(u_i, v_i; h) X_V && + \varepsilon_i && \text{(MGWR-SAR}(0, k_C, k_V)) \\
 y_i &= \rho(u_i, v_i; h) W y + \beta_C X_C && + \varepsilon_i && \text{(MGWR-SAR}(1, k, 0)) \\
 y_i &= \rho(u_i, v_i; h) W y + \beta_V(u_i, v_i; h) X_V && + \varepsilon_i && \text{(MGWR-SAR}(1, 0, k)) \\
 y_i &= \rho(u_i, v_i; h) W y + \beta_C X_C + \beta_V(u_i, v_i; h) X_V && + \varepsilon_i && \text{(MGWR-SAR}(1, k_C, k_V))
 \end{aligned}
 \tag{4}$$

The last equation in (4) coincides with Eq. (3), a model with all spatially varying parameters (including the spatial autoregressive parameter). The values in parenthesis of MGWR-SAR (i_ρ, k_C, k_V) models denote i_ρ —the fact that ρ is constant (0) or spatially varying (1); k_C —the number of constant β s; k_V — the number of spatially varying β s; and $k = k_C + k_V$.

Apart from the OLS and SAR formulations, all models in (4) are based on the common idea of the GWR approach to estimate N local regressions by weighting the observations in the local regressions depending on their distance from the focal point (see, e.g., Chochoolatá, 2020). The GWR technique involves several key components, including the *kernel function* and the choice of *bandwidth parameter* h (for more details, see, e.g., Gollini et al., 2015):

- *The kernel function* determines the weight assigned to each observation based on its proximity to the target location. Commonly used continuous or discontinuous kernel functions are, e.g., Gaussian, Exponential, Box-car, Bi-square, or Tri-cube. These functions assign higher weights to observations closer to the target location and lower weights to those farther away, reflecting the spatial decay of influence.
- *The bandwidth parameter* h determines the spatial extent over which observations are considered in the regression estimation. It controls the size of the local neighborhood around each target location. Bandwidth selection methods include cross validation (CV), Akaike information criterion (AIC), and Bayesian information criterion (BIC).

In the empirical part of this paper, we estimate models based on the OLS, SAR, and MGWR-SAR($1, k_C, k_V$) specifications defined in (1)–(3). As for the estimations of all MGWR-SAR models, we chose Gaussian kernel weighting function and the bandwidth parameter h is calibrated by CV optimization procedure.

The MGWR and MGWR-SAR approaches allow us to make a combination of spatially stationary and non-stationary parameters. This may be appropriate when modelling regional innovation, as the occurrence of spatial heterogeneity may not

apply to all parameters. It may happen that some innovation inputs may influence innovation output globally, with the strength of their impact on innovation output being the same in each region, while other parameters may vary spatially. In all MGWR-SAR models, a spatially lagged dependent variable (either constant $\rho W\mathbf{y}$, if $i_\rho = 0$ or spatially varying $\rho(u_i, v_i; h)W\mathbf{y}$, if $i_\rho = 1$) is present. This raises an endogeneity problem. In order to deal with the endogenous part of the model, all MGWR-SAR models are estimated by a spatial two-stage least square (S2SLS) technique with \mathbf{X} and \mathbf{WX} as a set of instruments. In the same way as the MGWR-SAR model, we estimate the SAR models in this paper. More details concerning to the topics of S2SLS and MGWR-SAR estimations can be found in Geniaux and Martinetti (2018) and Anselin and Rey (2014).

Finally, we briefly present a formulation of a regional knowledge production function (RKPF) model. By estimating the RKPF model, it is possible to study the contribution of innovation inputs to the production of regional innovation. The general form of this model takes the form (Moreno et al., 2005a):

$$I_i = f(\mathbf{R}_i, \mathbf{Z}_{1i}, \mathbf{Z}_{2i}, \varepsilon_i), \quad \forall i \in \{1, \dots, N\}, \quad (5)$$

where I represents an innovation output proxy, \mathbf{R} denotes a vector of regional R&D inputs, \mathbf{Z}_1 contains variables reflecting institutional and economic determinants, \mathbf{Z}_2 includes external regional factors, and ε is an error term.

Results

Based on the models defined by Eqs. (1) to (3) and the RKPF concept defined by Formula (5), we estimate several econometric models. In all models, irrespective of the innovation outputs, regional innovation is a function of innovation inputs: the top 10% most-cited publications, R&D expenditure in the business sector, human resources in science and technology, and population density. Additionally, regardless of the innovation outputs, we initially perform a global OLS estimation and subsequently consider all relevant spatial aspects (SAR and MGWR-SAR estimations). The estimates of the global OLS and SAR models serve as the basic starting point of our analysis and are performed solely to assess the stability and reliability of the empirical results under different model specifications. However, the primary focus will be on MGWR-SAR models.

To account for additional regional characteristics, in all models, we include dummy variables for lagging (less developed) regions (for variable descriptions, see Table 5). Human capital is widely recognized as a key determinant of innovation, yet, as noted by Diebolt and Hippe (2019), its long-term impact on innovation and economic development remains underexplored, particularly at the regional level. Therefore, we investigate whether human resources and a dummy variable reflecting lagging regions interact to influence regional innovation. This entails considering the possibility that both intercepts and slope parameters may vary between the two groups of regions. These dummy variables have a global character, applying not only to the global OLS and SAR estimations but also to MGWR-SAR models.

Specifically, we assume MGWR-SAR models with spatially varying parameters (including a spatial autoregressive parameter), with the exception of the dummy variables. In estimating the MGWR-SAR model, we employ a Gaussian weighting scheme, with the bandwidth parameter calibrated using the cross-validation optimization method, resulting in $h=3.6073$. All SAR and MGWR-SAR models presented in the paper are estimated using the S2SLS technique.

Model Estimates—Patent applications

The OLS1 and SAR1 model estimates (refer to Table 12 in the Annex) show that patent applications are positively influenced by most innovation determinants, except for population density, which surprisingly has a negative impact, contrary to previous findings (e.g., Knudsen, 2007). This suggests that factors influencing innovation outcomes may differ for patents as an innovation proxy. Human capital is confirmed as a significant driver of innovation, but lagging regions may lack advanced labor in science and technology, leading to lower innovation output. The negative coefficient of the interactive dummy variable highlights the disparities between lagging and other regions. However, the positive coefficient of the second dummy variable for lagging regions indicates stronger patenting activity in these areas. In the SAR1 spatial model, which includes a spatial lag of patent applications, significant spatial autocorrelation is evident, as indicated by the positive spatial autoregressive parameter ρ . This implies positive spatial innovation spillovers⁸ affecting regional patent applications. Given these findings, addressing spatial autocorrelation is crucial, supported by the *A-K* test (see Anselin & Rey, 2014), which confirms the suitability of SAR estimation (refer to Table 12 in the Annex for details).

Next, to examine both spatial effects simultaneously, the MGWR-SAR model was applied to model the European innovation problem. The initial examination of the MGWR-SAR1 model results (see Table 6) suggests the importance of the region's geographical position on the innovation process within the region. Basic statistics are provided in Table 6. Larger differences between the minimum and maximum values of the estimated parameters underscore spatial non-stationarity across the analyzed regions, indicating how the magnitude of a given innovation input varies across European regions, including changing signs of estimated parameters. The impact of almost all innovation inputs on patent activities was predominantly positive within the analyzed regions. However, the minimum values of all estimated parameters were negative. Similar to the OLS1 and SAR1 estimates (refer to Table 12 in the Annex), the population density factor exhibited negative values, and these negative values were observed up to the third quartile, with significance confirmed in over 50% of cases. Human resources also emerged as a significant source of innovation for more than half of European regions. Following the MGWR-SAR1

⁸ It must be kept in mind that the SAR model allows for global spillover effects and, therefore, the model estimates cannot be interpreted as in the classical regression model because the relevant feedback effects would not be captured. Given the scope of the paper and because we focus attention on the MGWR-SAR models, the corresponding summary measures of direct, indirect, and total impacts are not presented (see, e.g., LeSage & Pace, 2009).

Table 6 Estimation results generated by MGWR-SAR1 model

Variable	MGWR – SAR1 (PCT applications)						
	Min	First quartile	Median	Mean	Third quartile	Max	Percent of significant cases at 95%
Intercept	-1.2821	-0.2166	-0.1665	-0.1426	-0.0564	0.0837	89.09%
Most-cited publications	-0.4673	0.0190	0.0850	0.1253	0.1895	1.0541	37.27%
R&D expenditure in the business sector	-0.0646	0.2849	0.4990	0.4300	0.5638	1.2646	90.45%
Human resources in science and technology	-0.3117	-0.0298	0.1083	0.1010	0.2095	1.5870	54.55%
Density	-15.1429	-0.2654	-0.2098	-0.2943	-0.0243	0.2612	52.50%
DUM (lagging regions)	-0.0076						
DUM (lagging regions)×human resources in science and technology	-0.0483						
Spatial Lag	-0.0767	0.4080	0.4795	0.4413	0.5216	0.6150	92.27%
AIC	-411.522						

estimates, R&D expenditure in the business sector was identified as the most crucial determinant of regional patent activities, with its statistical significance confirmed in up to 90.45% of regions. Finally, the number of scientific publications proved to be a significant determinant of regional patenting activity in 37.27% of cases. The global nature of the two parameters associated with dummy variables did not indicate statistically significant differences between lagging regions and others, contrasting with global SAR1 estimation. However, the MGWR-SAR1 estimate suggests that spatial regional interactions significantly enhance regional innovation output, with a very high percentage of significant cases of the spatial autoregressive parameter (92.27%) providing support for this hypothesis.

Model Estimates—Trademark Applications

Now, we consider trademark applications as a proxy for innovation output. Both global estimates OLS2 and SAR2 (refer to Table 13 in the Annex) suggest differences in terms of various innovation outputs compared to patents. If we consider trademark applications as a proxy for innovation output, we observe that only R&D expenditure and population density play important roles in increasing the innovation output defined in this manner. Even spatial spillover effects within the dependent variable do not appear to be significant based on the global spatial model. However, when we implement local regressions using the MGWR-SAR2 model (see Table 7), we observe sharp differences compared to the global SAR estimate. Based on the MGWR-SAR2 estimate, all assumed innovation determinants (with spatially varying parameters) contribute significantly to generating regional trademarks. This finding is supported by a high percentage of significant cases (see Table 7). Regarding global variables, similar to the previous case of patents, both parameters corresponding to the dummy variables are statistically insignificant.

A previous estimate of the SAR model (see Table 13 in the Annex) did not indicate the adequacy of spatial spillovers within the dependent variable. However, the results of MGWR-SAR2 suggest that innovation inputs and trademarks are not only local in nature, but their positive effects may extend beyond the region. One explanation may be that the previous SAR model is a global model and may be limited when spatial processes change within a spatial context. There may also be an issue with the formulation of the spatial autoregressive model at the global level. From the results, we can observe that even after estimating the spatial model, the issue of remaining autocorrelation (*A-K* test) persists (see Table 13 in the Annex). The *LM* statistics indicate the presence of a spatial autoregressive process, but within a spatially lagged error term. In empirical applications, the presence of unobserved local or regional variables can lead to spatial error correlation. It is in local regressions where the individuality of regions is captured. Furthermore, if local regressions can also capture spatial regional interactions, they significantly enhance the global spatial estimate. This seems to be the case, although the different nature of the innovation output (trademarks) may also require additional variables to explain the innovation process.

Table 7 Estimation results generated by MGWR-SAR2 model

Variable	MGWR – SAR2 (Trademark applications)							Percent of significant cases at 95%
	Min	First quartile	Median	Mean	Third quartile	Max		
Intercept	-1.3010	-0.2058	-0.1135	-0.1352	-0.0590	0.5861	60.00%	
Most-cited publications	-0.3667	-0.0143	0.1452	0.1680	0.2374	1.3611	41.82%	
R&D expenditure in the business sector	-0.1278	0.1716	0.2656	0.2861	0.3401	0.9186	89.55%	
Human resources in science and technology	-2.5630	0.2095	0.4352	0.2846	0.5951	1.5871	83.64%	
Density	-3.8454	-0.0783	0.1890	0.4263	0.4312	8.7002	75.45%	
DUM (lagging regions)	0.0888							
DUM (lagging regions)×human resources in science and technology	-0.2327							
Spatial lag	-0.7941	0.0771	0.3085	0.3080	0.4639	2.3853	53.18%	
AIC	-238.0779							

Model Estimates—Design Applications

Finally, design applications are considered innovation output. Again, global estimates OLS3 and SAR3 (refer to Table 14 in the Annex) point to some differences in results, mainly compared to patents. Based on the OLS3 estimate, only one statistically significant innovation factor is identified, namely R&D expenditure. Similarly, the SAR3 model estimate identifies only one internal innovation determinant, namely the most-cited publications. The spatial interconnection of European regions has already been proven based on the global SAR model (statistical significance of the spatial autoregressive parameter), and the problem of remaining spatial autocorrelation was rejected.

Next, we proceed with the simultaneous examination of spatial autocorrelation and heterogeneity. The implementation of local regressions, i.e., the MGWR-SAR3 model (see Table 8), reveals differences compared to the global SAR estimate. Based on the MGWR-SAR3 estimate, all innovation determinants (with spatially variable parameters) appear to be important in generating regional design applications. This finding supports a relatively high percentage of significant cases (see Table 8) for all inputs. Regarding global variables, as in previous patents and trademarks cases, both parameters corresponding to dummy variables are statistically insignificant.

We find similarity in the MGWR-SAR model estimates for trademarks and designs. The magnitudes of spatial autoregressive parameters (in terms of absolute values) are similar (see statistics in Tables 7 and 8); for instance, the median value is approximately 0.3 in both MGWR-SAR models. Also, the number of statistically significant cases is very similar (about 50%). In terms of patent activities, up to 92.27% of European regions exhibit a significant relationship with neighboring regions, and the strength of spatial dependence is higher. Overall, interregional links and resulting spatial spillovers appear to be strong external factors of innovation, regardless of innovation output.

The estimates of all local parameters are depicted in the natural break maps (presented in the Annex) and box plots in the following subsection. More detailed attention will be given to them when comparing results related to all three innovation outputs.

Table 8 Estimation results generated by MGWR-SAR3 model

Variable	MGWR – SAR3 (Design applications)						
	Min	First quartile	Median	Mean	Third quartile	Max	Percent of significant cases at 95%
Intercept	-1.2146	-0.0571	0.1182	0.1133	0.3323	0.5107	57.27%
Most-cited publications	-1.1413	-0.1752	-0.0023	0.1045	0.2167	1.4638	42.73%
R&D expenditure in the business sector	-0.1406	0.1914	0.2917	0.3264	0.385	1.0452	74.55%
Human resources in science and technology	-1.6472	-0.3042	0.0062	-0.0783	0.2108	1.2903	57.27%
Density	-14.2467	-0.2558	-0.0986	-0.1546	0.2269	4.1506	47.27%
DUM (lagging regions)	-0.0014						
DUM (lagging regions) × human resources in science and technology	-0.0007						
Spatial lag	-0.8576	0.0072	0.2929	0.3398	0.6888	2.2591	50.45%
AIC	-148.0534						

Comparison of Innovation Determinants in Relation to Different Innovation Outputs

Now, we delve into the heterogeneous impacts of innovation inputs in greater detail. The MGWR-SAR estimates for the three distinct innovation outputs offer local estimates for all regions, facilitating the analysis of potential disparities in the effects of individual innovation determinants across regions and across different innovation outputs. To compare the distribution of local parameter estimates among the three considered innovation outputs, we present box maps (refer to Figs. 9, 10, 11, 12 and 13 in the Annex) and box plots alongside the corresponding summary statistics (Figs. 4, 5, 6, 7 and 8). A summary of the results regarding the significance of local parameters is provided in Table 9.

Figure 9 (see Annex) and Fig. 4 display a comparison of local parameter estimates for the first innovation input—the most cited publications. The box plots in Fig. 4 provide an initial impression suggesting that there is no difference between patents and trademarks, as their boxes (representing the interquartile range) roughly overlap. The outliers (points outside the whiskers) and the size of the whiskers indicate the range and variability of the effects. Unlike patents, trademarks are characterized by larger ranges and a higher number of upper outliers. Based on Fig. 9 (see Annex) and Fig. 4, we observe several other similarities. For example, the regions identified as upper outliers (Norwegian and Spanish regions) coincide in trademarks and designs. However, at the same time, the Norwegian regions were identified as lower outliers in terms of patents. Overall, the responses of the three innovative outputs to the change in scientific publications appear to be heterogeneous within European regions, and differences are also observed across different outputs.

Based on Fig. 10 (see Annex) and Fig. 5, we can observe the spatial distribution of estimated R&D expenditure parameters. Firstly, it should be noted that according to our analysis, R&D expenditure emerges as the most critical innovation determinant, in terms of both magnitudes and the number of statistically significant regions (for patents and trademarks, more than 90% regions and 74.55% for design applications). We find a greater similarity in terms of the magnitude of the R&D expenditure effects on trademarks and designs; the boxes (see Fig. 5) almost overlap, while the range and variability of the effects are similar (e.g., similar median values, 0.2656 for trademarks; 0.2917 for designs). Even in the context of outliers, both upper and lower, there is similarity. The upper outliers are mainly the Scandinavian regions, the Spanish and Portuguese regions, while the Irish regions are included among the lower outliers (refer to Fig. 10 in the Annex). As for patents, the median line of the box (0.499) lies outside the boxes for trademarks and designs. Thus, there is likely a significant difference between patents and the two previous innovation outputs. The magnitude of the effects of R&D expenditure is significantly higher in the case of patents.

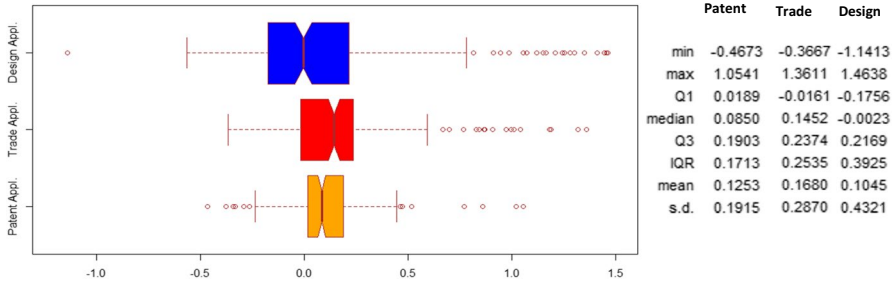


Fig. 4 Box plots of local parameter estimates - Most-cited publications

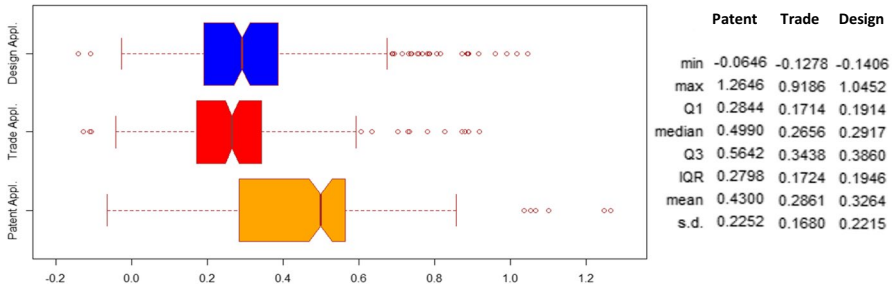


Fig. 5 Box plots of local parameter estimates - R&D expenditure

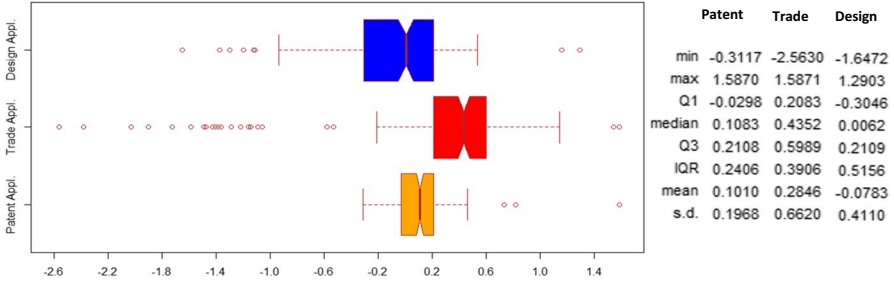


Fig. 6 Boxplots of local parameter estimates - Human resources in science and technology

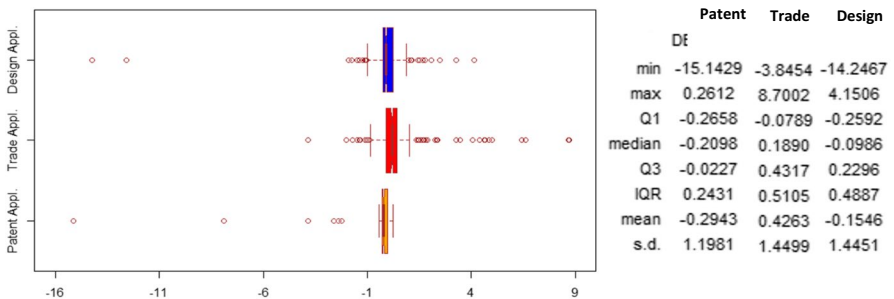


Fig. 7 Box plots of local parameter estimates - Density

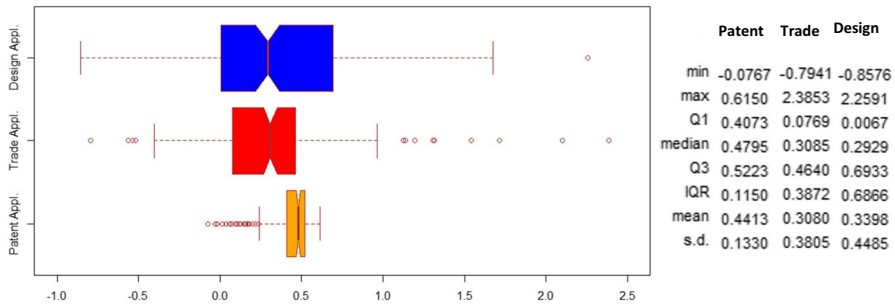


Fig. 8 Box plots of local parameter estimates - Spatial autoregressive parameter

Next, we turn our attention to human resources in science and technology. The disparities in the local parameter estimates for this innovation input are evident from the maps and box plots depicted in Fig. 11 (see Annex) and Fig. 6, respectively. Once again, significant variations in the estimated parameters across European regions, as well as in terms of different innovation outputs, are noticeable. From a statistical standpoint, human resources as an innovation determinant is highly significant in the case of trademarks (83.64% of regions). Additionally, the influence of this factor in individual regions is substantial; for instance, the median value is several times higher than in the case of patents and designs (median values, 0.1083 for patents; 0.4352 for trademarks; 0.0062 for designs). When examining patents and design applications, the human resources factor emerges as a significant innovation determinant in more than half of European regions (see Table 9). A certain similarity can be observed when comparing the results pertaining to these two outputs. The boxes in the box plots (see in Fig. 6) roughly overlap with one another. However, the size of the whiskers indicating the range and variability point to a difference between the two estimates. Unlike patents and designs, trademarks are characterized by a higher number of lower outliers. What is common to all three considered innovation outputs is that some Scandinavian regions are again included in the group of upper outliers, while the Spanish regions are lower outliers (refer to Table 11 in the Annex).

Based on our econometric analysis, the population density factor emerges as a contentious innovation determinant, particularly concerning patents and design applications. Despite the high number of statistically significant cases (50% of regions, see Table 9), the prevailing unexpected negative values of estimated parameters for patents and designs are noteworthy (see Fig. 10 in the Annex and Fig. 7). Notably, median value for designs is negative, and even patents show negative values up to the third quartile. However, for trademarks, the picture differs. The population density factor significantly influences regional trademark activities, with 75.45% of regions demonstrating significance. Trademarks exhibit a notable number of upper outliers. Overall, the results suggest a substantial impact of population density on trademarks, as evidenced by a median value of 0.1890.

Based on the MGWR-SAR estimates, we can deduce insightful observations about spatial interactions influencing innovation activities across European regions. Specifically, the spatial autoregressive parameter varies significantly across the

European area (see Fig. 13 in the Annex and Fig. 8) for all three outputs. Notably, this parameter is statistically significant in the majority of European regions (92.27%) for regional patenting activities. While spatial interactions are less pronounced for trademarks and designs (approximately 50% of regions, see Table 9), the interconnectedness of regions remains a significant factor in enhancing these innovation outputs. The magnitude of this factor on the regional innovation output appears to be substantial, with median values of 0.4795 for patents, 0.3085 for trademarks, and 0.2929 for designs (see Fig. 8).

Discussion

In the preceding sections, our focus was on the technical discussion of model estimates. Now, we pivot our attention towards interpreting and drawing implications from these results.

Our study utilizes MGWR-SAR estimates to examine the disparities in the effects of innovation determinants on three distinct innovation outputs—patents, trademarks, and design applications across European regions. Through this analysis, we uncover intriguing insights into the heterogeneous influence of innovation inputs on different innovation outputs.

The diverse responses of innovation outputs to innovation inputs, coupled with the differing significance of these inputs in individual models, underscore the importance of employing multiple metrics to measure innovation output, rather than solely relying on patents. This finding aligns with previous studies, where patents have been conventionally considered the primary indicator of regional innovation due to their legal protection of inventions. However, it is essential to recognize that designs and trademarks play complementary roles in capturing different facets of innovation.

Drawing on prior research (Charlot et al., 2015; Flikkema et al., 2014; Halásková & Bednář, 2023; Hervas-Oliver et al., 2021; Lopes et al., 2021; Moreno et al., 2005a; Paci et al., 2014; Parent & LeSage, 2008; Popescu et al., 2023; Ribeiro et al., 2022), various methods have been employed to assess regional innovation performance. While patent applications are commonly accepted as the primary proxy for innovation output, other indicators such as small- and medium-sized

Table 9 MGWR-SAR result comparison

Variable	Percent of significant cases at 95%		
	Patent applications	Trademark applications	Design applications
Intercept	89.09%	60.00%	57.27%
Most-cited publications	37.27%	41.82%	42.73%
R&D expenditure in the business sector	90.45%	89.55%	74.55%
Human resources in science and technology	54.55%	83.64%	57.27%
Density	52.50%	75.45%	47.27%
Spatial lag	92.27%	53.18%	50.45%

enterprise (SME) introducing product or process innovations, trademarks, and design registrations, as well as regional innovation scores, are also utilized.

Despite the predominant focus on patents in many studies, trademarks have emerged as significant complementary indicators of innovation (Mendonça et al., 2004; Gotsch & Hipp, 2012; Flikkema et al., 2014). Trademarks are integral to marketing efforts and often accompany the introduction of innovative products or services, particularly in service and knowledge-intensive sectors. Ribeiro et al. (2022) emphasize the importance of incorporating trademark data alongside patents to comprehensively understand innovation processes, highlighting a strong correlation between trademarks and patents across various contexts. These studies emphasize the necessity of integrating trademark data into innovation studies to effectively capture diverse forms of innovation.

Overall, patent applications are usually more influenced by factors such as tax policies, legal frameworks, and administrative procedures, due to their technical nature and significant investment in their development. For example, countries offering tax incentives or simplified administrative processes for research and development activities may attract more patent applications, especially in technology-intensive sectors. In addition, information on the location of the patent is also problematic, since the regional statistics of the European Patent Office (EPO) are based on the address of the patent owner, which may not coincide with the place of implementation of the innovation (Moser, 2013).

Unlike patents, trademarks and designs may be less sensitive to tax and administrative strategies because they are often associated with branding and visual elements rather than technical innovations. While trademarks and designs can still benefit from a supportive tax and administrative environment, their registration and protection processes are generally less complex and costly compared to patents.

In the context of regional innovation modeling across European regions, the mixed geographically weighted regression (MGWR) approach, coupled with the spatial autoregression (SAR) model, provides clear advantages over traditional spatial econometric models such as SAR. In our study, unlike others that relied on traditional or spatial econometric approaches, we find this methodology to be uniquely beneficial and distinctive. MGWR allows for the examination of innovation determinants that vary geographically across European regions. This local flexibility is crucial in capturing the diverse innovation dynamics present within different regions. European regions exhibit substantial diversity in terms of economic development, industrial specialization, and innovation systems. The MGWR-SAR framework can accommodate this diversity by providing tailored parameter estimates for each region, leading to improved model fit compared to traditional SAR models that assume uniform relationships across space.

In our analysis, regardless of the innovation outputs considered, we include traditional innovation inputs such as scientific publications, R&D expenditure in the business sector, human resources in science and technology, and population density. Additionally, we incorporate the effect of lagging regions into the models through dummy variables. Our MGWR-SAR estimates reveal a spatial heterogeneity issue, highlighting that MGWR can effectively capture the relationships between innovation inputs and outputs across European regions.

Our results⁹ suggest that high-quality scientific publications play a relatively strong role as an innovation determinant across all the outputs under consideration. Presently, the engagement of firms in academic research activities is increasingly common and appears to enhance their innovation performance. The dissemination of scientific discoveries is facilitated through publications in scientific journals. However, the significance of this innovation input diminishes to approximately 40% in comparison with other inputs considered (see Table 9), and its impact varies across regions and innovation outputs.

R&D expenditure emerges as the most important innovation determinant, significantly influencing patents and trademarks in more than 90% of regions. The efficiency of R&D expenditure varies across regions⁹, with Scandinavian regions demonstrating higher efficiency compared to post-socialist regions. This suggests the need for targeted policies to enhance R&D efficiency, particularly in lagging regions.

In conclusion, human resources in science and technology play a significant role in driving innovation across European regions, particularly notable in trademarks, where 83.64% of regions exhibit significance. The median values for trademarks notably exceed those for patents and designs, emphasizing the substantial impact of human resources. While patents and designs also demonstrate the significance of human resources in over half of European regions, trademarks show lower outliers. The consistent presence of Scandinavian regions as upper outliers across all three outputs, along with the prevalence of Spanish regions as lower outliers⁹, underlines regional disparities in innovation drivers.

The population density factor presents a controversial determinant, especially in relation to patents and design applications. While its significance is high in terms of trademarks, unexpected negative values are observed for patents and designs in certain regions.

We have already concluded that R&D expenditure appears to be the most influential innovation determinant. However, spatially lagged innovation output also seems to play a significant role, particularly when its impact intensity on the region's innovation output is substantial (median values, 0.4795 for patents; 0.3085 for trademarks; 0.2929 for designs). The model estimates from all three MGWR-SAR models indicate that regional innovation is influenced by spatial spillovers, and that individual spatial processes drive innovation in each region rather than a uniform spatial process across the entire area. When comparing results among different innovation outputs⁹, significant differences emerge. For instance, patents show a large number of lower outliers in regions like Spain and Portugal, whereas these same regions exhibit a high intensity of spatial spillovers in connection with trademarks. Another example is seen in Finnish and Swedish regions, which show some of the highest values of spatial autoregressive parameters in connection with designs, while simultaneously representing lower outliers in the patent model.

⁹ See box maps of local parameter estimates in Annex.

The results presented here were based on estimates from MGWR-SAR models, and the global SAR model served as a robust check of the main findings. We found some differences, but this can be expected since MGWR-SAR incorporates local regressions. Therefore, for example, the effect of lagging regions was not evident in any of the MGWR-SAR models, and we assume that the local nature of the regressions contributed to this.

Comparison of these results with the findings of other similar studies regarding the heterogeneity of MGWR-SAR model parameters or spatial autoregressive parameters is not directly possible, as a comparable methodology for modeling regional innovation processes has not yet been applied.

Our findings, which are consistent with all our stated hypotheses, suggest the importance of integrating trademark and design data into innovation studies in order to effectively capture different forms of innovation. In addition, the findings are in line with the conclusions of other innovation studies, as the studies listed in Table 10 (see Annex) highlight the important role of geographical proximity in fostering the creation of innovations within regions and facilitating knowledge exchange and cooperation between local actors.

Conclusions

The aim of this study is to identify the main determinants influencing European regional innovation represented in three different ways: patent, trademark, and design applications. The newly proposed MGWR-SAR approach is served as the main tool for addressing the research questions. The initial estimations were based on global OLS and SAR models, followed by MGWR-SAR estimations. All innovation inputs (most-cited publications, R&D expenditure in the business sector, human resources in science and technology, and population density) were found to be essential across all three MGWR-SAR models. These determinants were statistically significant factors in the majority of European regions, except for most-cited publications (relevant for about 40% of regions). Moreover, their impact could extend beyond regional boundaries, indicating spatial diffusion. Another significant finding pertains to the spatial heterogeneity of model parameters, suggesting variations in the strength of innovation determinants among regions. All MGWR-SAR models show that the strength of innovation determinants might vary among regions. While all selected innovation inputs were found to increase all three innovation outputs, differences emerged when considering different proxies for regional innovation.

As innovation output can be defined in various proxies, regional R&D and innovation strategies should account for the specifics of each. Trademarks and designs, alongside patents, represent distinct aspects of innovation activity and are prevalent in different sectors. Policymakers must tailor their approaches based on the targeted sector, given that patents are more common in manufacturing, while designs and trademarks are prevalent in services. The varying responses of innovation outputs

to innovation inputs, coupled with the differing significance of these inputs in individual models, emphasize the importance of employing multiple metrics to measure innovation output, rather than relying solely on patents.

In general, the MGWR-SAR approach seems to be a suitable spatial econometric tool when simultaneously addressing spatial autocorrelation and heterogeneity. This study represents the first analysis of the European regional innovation problem considering spatial effects based on the MGWR-SAR approach, with different innovation outputs as modeled variables.

Overall, the MGWR-SAR approach provides a sophisticated framework for modeling regional innovation in European regions, offering insight into spatial spillovers, spatially varying relationships, thereby addressing spatial autocorrelation and heterogeneity simultaneously. This may facilitate informed policymaking to promote innovation-led regional development.

Policy Implications

The various institutional frameworks, policies, funding mechanisms, and regulations within EU Member States can have a significant impact on innovation dynamics and outcomes. At the EU level, initiative such as Horizon Europe (European Commission, 2024) provides main framework and funding support to boost innovation across Member States. Horizon 2020, the EU's research and innovation program from 2014 to 2020, had a budget of €80 billion. Its successor, Horizon Europe (2021–2027), has a budget of €95.5 billion, focusing on climate change, sustainable development, and boosting competitiveness Europe (European Commission, 2024). It promotes collaboration, job creation, and open science. The European Innovation Council (EIC) has been established under the EU Horizon Europe programme. It supports game changing innovations throughout the lifecycle from early-stage research, to proof of concept, technology transfer, and the financing and scale up of start-ups and SMEs. Legal entities from the EU and associated countries can participate, fostering a stronger European Research Area (ERA) and strategic partnerships with industry.

Additionally, the EU's cohesion policy allocates funds to reduce disparities and promote balanced development across regions, including investments in innovation infrastructure and capacity-building initiatives. Individual EU countries develop and implement national innovation policies adapted to their unique context, in accordance with EU directives and at the same time address specific national priorities. These policies may involve strategies to stimulate research and development through government grants, tax incentives, and public–private partnerships. Furthermore, legal and regulatory frameworks govern intellectual property rights, including patents, trademarks, and designs, ensuring innovators are adequately protected and incentivized.

The MGWR-SAR estimates gave us a local view of all regions, allowing regional individuality or specific groupings to be considered. For instance, lagging regions, which receive long-term EU funding assistance, can be analyzed separately, potentially revealing less effective innovation inputs compared to advanced regions. This

differentiated approach is crucial as it prevents potential disparities from widening due to poorly defined innovation policies, especially if policies focus solely on increasing R&D spending, which may disproportionately benefit prosperous regions. Therefore, our findings underline the importance of analyzing the heterogeneous effects of innovation inputs within regions to ensure effective regional policy strategies and the efficient use of available funds.

Furthermore, the EU cohesion policy emphasizes cross-border cooperation among EU regions and extends its focus to include even the outermost regions, aiming to improve regional performance through various policy instruments and programs supporting such cooperation. In addition, spillover effects can extend beyond the supported areas, benefiting other regions as well. An important aspect highlighted by our analysis concerns spatial interregional interactions, particularly evident in patent activities, which demonstrate high spatial connectivity between regions, with a significant relationship confirmed in 92.27% of regions. This suggests that external innovation determinants from neighboring regions can significantly enhance regional innovation. Consequently, innovation strategies should prioritize the development of interregional cooperation and support for companies engaged in interregional and international knowledge networks.

At the EU policy level, cluster policy occupies an important position. Once again, the local parameter estimates and different innovation measures offer an option to perform more place-based policy strategies. The interest of policymakers may not be focused exclusively on the best performing regions but lagging regions, metropolitan-hub areas, specific sectors, or a specific group of actors may also be targeted. The presence of clusters in regions is correlated with stronger innovation behavior of the region and consequently contributes to the increase of innovations in the region. In this sense, a strong innovation cluster of universities, research institutions, and SMEs seem to be very beneficial and cluster and innovation policies should support the establishment of such cluster organizations to promote cooperation between cluster actors (Franco et al., 2021). However, the implementation of the policy should be conditioned by considering the industry sector, which will clarify the expected form of innovation outputs. Subsequently, different effects of innovation inputs, which are conditioned by both the expected output and regional disparities, might be considered. This valuable information can be derived from local regressions based on the MGWR-SAR model.

Finally, in discussing policy implications, it is important to mention the concept of path dependency, which underlines how historical trajectories and existing structures can significantly influence future outcomes. Given the indication of spatial regional interconnections in our findings, which might lend support to concentration policies, it is beneficial to explore strategies that counterbalance this tendency. One way for consideration involves implementing policies aimed at exerting control by sector in each region, ensuring that innovation efforts are diversified and not overly concentrated in specific industries or areas. Since our analysis does not rely solely on patents but assumes that the innovation output of the region can be shaped by multiple types of innovation, we can refine innovation policies and regulations even further. In the EU context, the sector-specific regulation directly affects innovation in a way that depends mostly on the stringency, timing, flexibility, and uncertainty

generated by the rules at hand (Pelkmans & Renda, 2014). By promoting diversification and decentralization within innovation ecosystems, policymakers can mitigate the risks associated with excessive concentration.

Limitations and Future Research

In considering limitations and directions for future research, it is important to acknowledge the constraints of the current study and identify areas that warrant further investigation. Improving the analysis may involve identifying other relevant factors determining regional innovation, especially considering the different innovation outputs. In this study, we utilized data from the Regional Innovation Scoreboard (RIS), which draws its data from various sources including Eurostat, the European Patent Office, the European Union Intellectual Property Office, and other international organizations and databases. In further research, we aim to leverage this data source to explore the relevance of additional innovation determinants and delve into the specifics of the considered innovation outputs. However, it is challenging to consider and identify all relevant factors influencing innovation processes at a regional level due to the limited availability of data at the NUTS2 level.

The RIS provides multi-period data, but their applicability within the context of the applied MGWR-SAR methodology is currently restricted as there is no extension of MGWR-SAR models available to handle spatial panel data. Additionally, this new approach does not allow for the estimation of other specifications of spatial econometric models beyond the SAR model. Moving forward, an SEM model that implements spatial spillovers through a disturbance term would be beneficial.

Regarding the estimation aspects of the models, it is worth noting that we restricted ourselves to using the same kernel weighting function with the same bandwidth parameter setting. Therefore, alternative kernel weighting function schemes may need to be reconsidered along with addressing the issue of bandwidth parameterization, especially given the different proxies or measures used to indicate innovation.

In future research, we also intend to explore other methodologies proposed by Chen et al. (2022) and Wu et al. (2023) to address spatial autocorrelation and heterogeneity simultaneously.

Appendix

Table 10 Summarization of studies on European regional innovation processes with spatial spillovers using patents as innovation output

Paper			
Bottazzi and Peri (2003)	Number of regions	86 European regions	
	Time span	1977–1995 period	
	NUTS level	1,2	
	Innovation output	Patent applications	
	Methodology	Panel data models	
	Main findings	There are small positive externalities accrue to regions within 300 km from the region that employs the R&D resources	
Moreno et al. (2005a)	Number of regions	175 European regions	
	Time span	1978–2001 period	
	NUTS level	0,1,2	
	Innovation output	Patent applications	
	Methodology	Spatial Panel Data Models	
	Main findings	Spillovers are mostly constrained by national borders within less than 250 km	
		Number of regions	175 European regions
Moreno et al. (2005b)	Time span	Two periods: 1994–1996 and 1999–2001	
	NUTS level	0,1,2	
	Innovation output	Patent applications	
	Methodology	Panel data models	
	Main findings	Specialized innovative clusters are present and are getting stronger both within each country and across the whole Europe	

Table 10 (continued)

Paper			
Parent and LeSage (2008)	Number of regions	323 European regions	
	Time span	–	
	NUTS level	1,2	
	Innovation output	Patent applications	
	Methodology	Conditional spatial autoregressive model	
Autant-Bernard and LeSage (2011)	Main findings	The largest spillovers are for the most part taking place between a limited set of highly developed regions in Europe	
	Number of regions	94 metropolitan French regions	
	Time span	1992 to 2000 period	
	NUTS level	–	
	Innovation output	Patent applications	
Paci et al. (2014)	Methodology	Panel data models	
	Main findings	The spatial spillover effects from cross-industry private research are larger than spatial spillover effects from other types of R&D activity	
	Number of regions	276 regions (EU27 plus Norway, Switzerland)	
	Time span	–	
	NUTS level	2	
	Innovation output	Patent applications	
	Methodology	Spatial econometrics models	
	Main findings	Geography is not the only dimension which may help knowledge diffusion. Technological proximity is the most important one	

Table 10 (continued)

Paper			
Charlot et al. (2015)	Number of regions	25 EU regions	
	Time span	1995–2004 period	
	NUTS level	1,2	
	Innovation output	Patent applications	
	Methodology	Generalized additive model	
	Main findings	Geographical links matter for knowledge spillovers. R&D expenditure of neighboring regions have a positive impact on a region's invention performance for the central part of R&D distribution	
Hervas-Oliver et al. (2021)	Number of regions	220 European regions	
	Time span	2014–2017 period	
	NUTS level	1,2	
	Innovation output	SMEs' introducing product or process	
	Methodology	Logistic quantile regressions	
	Main findings	Regions in Europe differ significantly in terms of SME innovation depending on their location	
	Number of regions	European regions	
	Time span	2019	
	NUTS level	1,2	
	Innovation output	SMEs' introducing product or process	
Lopes et al. (2021)	Methodology	Discriminant analysis	
	Main findings	Specific innovation strategies explain the competitive positioning of economies within each group of countries	

Table 10 (continued)

Paper			
Halášková and Bednář (2023)	Number of regions	176 European regions	
	Time span	2014–2021 period	
	NUTS level	2	
	Innovation output	Summary Innovation Index	
	Methodology	Fixed effects panel data model	
	Main findings	Significant impact of public and private sector R&D indicators on innovation performance of Western European NUTS 2 regions	
Popescu et al. (2023)	Number of regions	154 European regions	
	Time span	2000–2020 period	
	NUTS level	2	
	Innovation output	Regional innovation score, patents applications	
	Methodology	Dynamic spatial panel data model	
	Main findings	EU regions tend to behave as competitors for investment fixing, but in the long run, innovation has the potential to generate spillover effects on neighboring regions	
Furková (2021)	Number of regions	220 European regions	
	Time span	2019	
	NUTS level	2	
	Innovation output	Patent applications	
	Methodology	Mixed geographically weighted regression–spatial autoregressive model	
	Main findings	Spatial heterogeneous responses of regional innovation output to innovation inputs and spatial spillovers have been indicated as a significant factor in increasing innovation	

Source: Own elaboration and Kijek and Kijek (2019)

¹Small- and medium-sized enterprise (SME)

Table 11 The top ten best performing regions—PCT applications, trademark applications, and design applications

	PCT applications			Trademark applications			Design applications		
	Region (NUTS codes)	Country		Region (NUTS codes)	Country		Region (NUTS codes)	Country	
1	Noord-Brabant (NL41)	Netherlands		Zentralschweiz (CH06)	Switzerland		Umbria (IT12)	Italy	
	Oberpfalz (DE23)	Germany		Ticino (CH07)	Switzerland		Jihozapad (CZ03)	Czechia	
	Sydsverige (SE22)	Sweden		La Rioja (ES23)	Spain		Ostschweiz (CH05)	Switzerland	
2	Stockholm (SE11)	Sweden		Helsinki-Uusimaa (FI1B)	Finland		Arnsberg (DEA5)	Germany	
3	Stuttgart (DE11)	Germany		Stockholm (SE11)	Sweden		Detmold (DEA4)	Germany	
4	Mittelfranken (DE25)	Germany		Berlin (DE30)	Germany		Marche (IT13)	Italy	
5	Helsinki-Uusimaa (FI1B)	Finland		Illes Balears (ES53)	Spain		Stuttgart (DE11)	Germany	
6	Oberbayern (DE21)	Germany		Hovedstaden (DK01)	Denmark		Veneto (ITH3)	Italy	
7	Ostra Mellansverige (SE12)	Sweden		Comunidad Valenciana (ES52)	Spain		Mittelfranken (DE25)	Germany	
8	Nordwestschweiz (CH03)	Switzerland		Sydsverige (SE22)	Sweden		Westosterreich (AT3)	Austria	
9	Karlsruhe (DE12)	Germany		Cataluna (ES51)	Spain		Wielkopolskie (PL41)	Poland	
10	Rhein Hessen-Pfalz (DEB3)	Germany		Hamburg (DE60)	Germany		Friuli-Venezia Giulia (ITH4)	Italy	

Source: Author's elaboration based on the Hollanders et al. (2019)

Table 12 Estimation results generated by OSL and SAR models—PCT applications

Variable	OLS1	SAR1
Intercept	-0.1691***	-0.1693***
Most-cited publications	0.2440***	0.1341**
R&D expenditure in the business sector	0.5899***	0.4914***
Human resources in science and technology	0.2898***	0.1536***
Density	-0.3498***	-0.2594***
DUM (lagging regions)	0.1265***	0.1237***
DUM (lagging regions)×human resources in science and technology	-0.5002***	-0.3911***
Spatial lag		0.4415***
R^2	0.7472	0.8113
Spatial pseudo R^2		0.7883
<i>AIC</i>	-314.465	-
Moran's <i>I</i> (residuals)	4.91***	
<i>LM(SAR)</i>	50.3119***	
Robust <i>LM(SAR)</i>	31.9960***	
<i>LM(SEM)</i>	18.4882***	
Robust <i>LM(SEM)</i>	0.1724	
Anselin–Kelejian (<i>A–K</i>) test		0.830

Parameters are statistically significant at ** p -value < 0.05; *** p -value < 0.01; *LM* Lagrange multiplier

Table 13 Estimation results generated by OSL and SAR models—trademark applications

Variable	OLS2	SAR2
Intercept	0.1199*	0.1073
Most-cited publications	0.0497	0.0387
R&D expenditure in the business sector	0.3190***	0.3102***
Human resources in science and technology	0.1516	0.1568
Density	0.3003**	0.3021**
DUM (lagging regions)	-0.0317	-0.0256
DUM (lagging regions)×human resources in science and technology	-0.0713	-0.0756
Spatial lag		0.0510
R^2	0.3390	0.3625
Spatial pseudo R^2		0.3387
<i>AIC</i>	-128.984	
Moran's <i>I</i> (residuals)	7.9007***	
<i>LM(SAR)</i>	45.353***	
Robust <i>LM(SAR)</i>	0.006	
<i>LM(SEM)</i>	54.266***	
Robust <i>LM(SEM)</i>	8.918***	
Anselin–Kelejian (<i>A–K</i>) test		4.134**

Parameters are statistically significant at * p -value < 0.1; ** p -value < 0.05; *** p -value < 0.01; *LM* Lagrange multiplier

Table 14 Estimation results generated by OLS and SAR models—design applications

Variable	OLS3	SAR3
Intercept	0.2290***	0.1096
Most-cited publications	-0.0012	-0.0293***
R&D expenditure in the business sector	0.3606***	0.2700
Human resources in science and technology	0.0215	-0.0113
Density	-0.0171	0.0072
DUM (lagging regions)	-0.1243	-0.0796
DUM (lagging regions) × human resources in science and technology	0.4161**	0.2769
Spatial lag		0.4642***
R^2	0.1972	0.3595
Spatial pseudo R^2		0.2228
<i>AIC</i>	-86.444	
Moran's <i>I</i> (residuals)	6.3634***	
<i>LM(SAR)</i>	41.120***	
Robust <i>LM(SAR)</i>	6.677***	
<i>LM(SEM)</i>	34.519***	
Robust <i>LM(SEM)</i>	0.077	
Anselin – Kelejian (<i>A-K</i>) test		0.105

Parameters are statistically significant at ** p -value < 0.05; *** p -value < 0.01; *LM* Lagrange multiplier

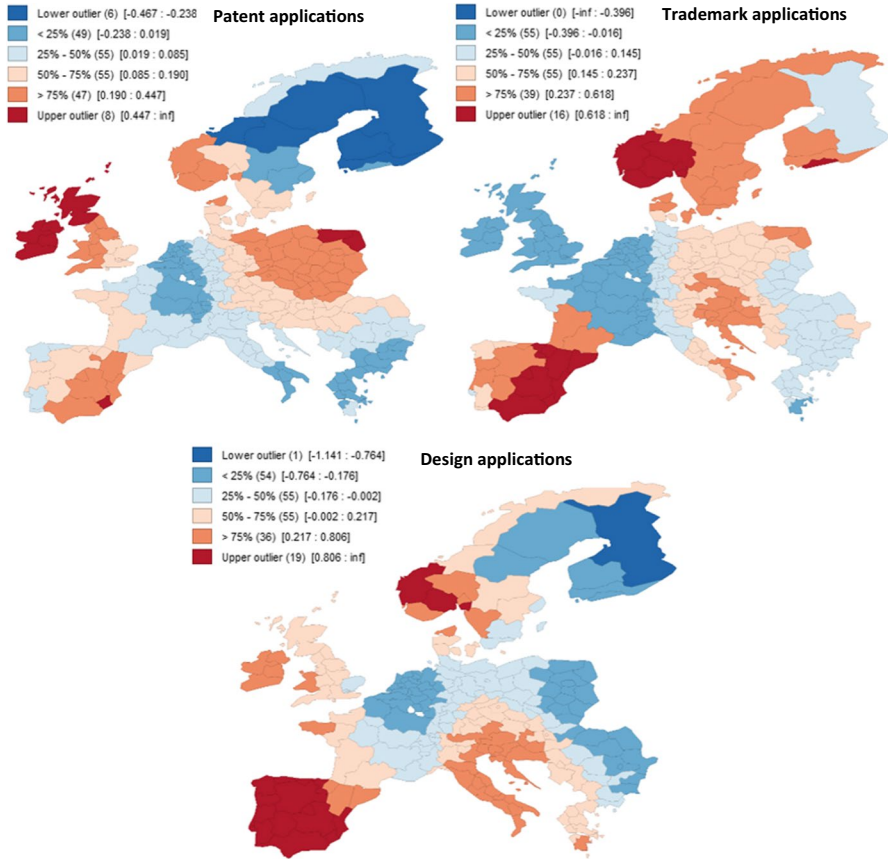


Fig. 9 Box maps of local parameter estimates - Most-cited publications

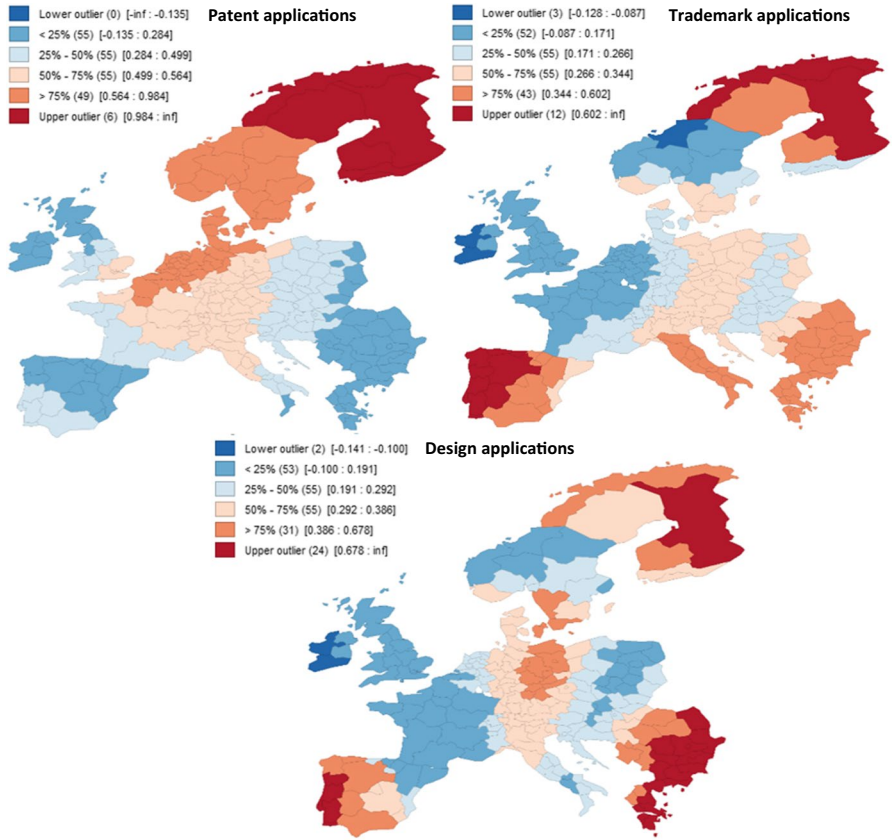


Fig. 10 Box maps of local parameter estimates - R&D expenditure

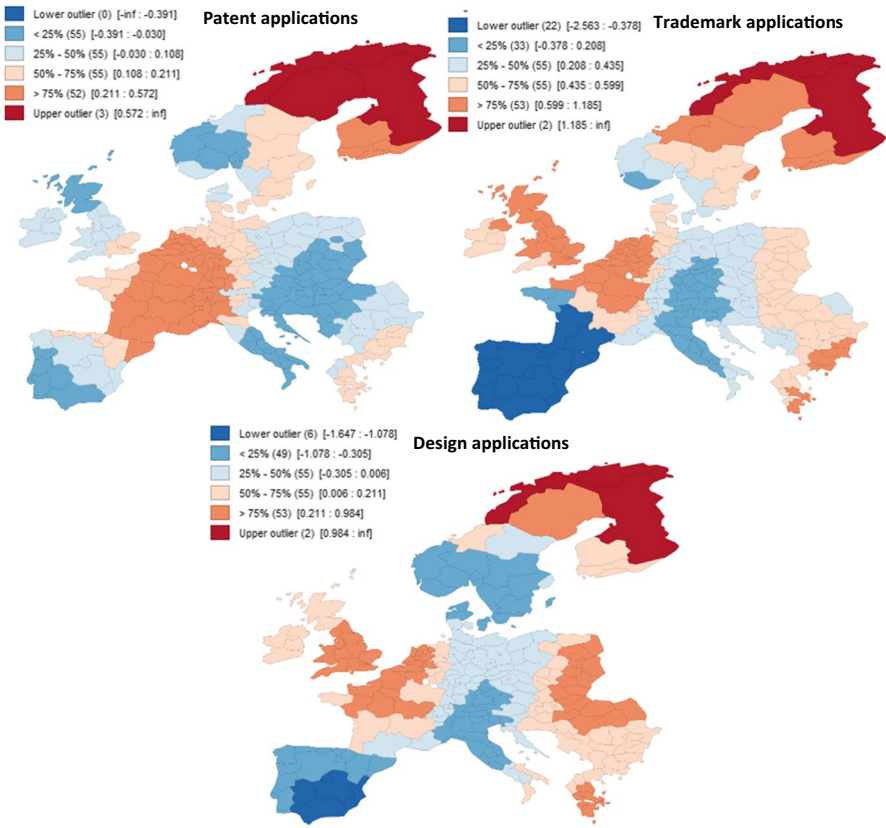


Fig. 11 Box maps of local parameter estimates - Human resources in science and technology

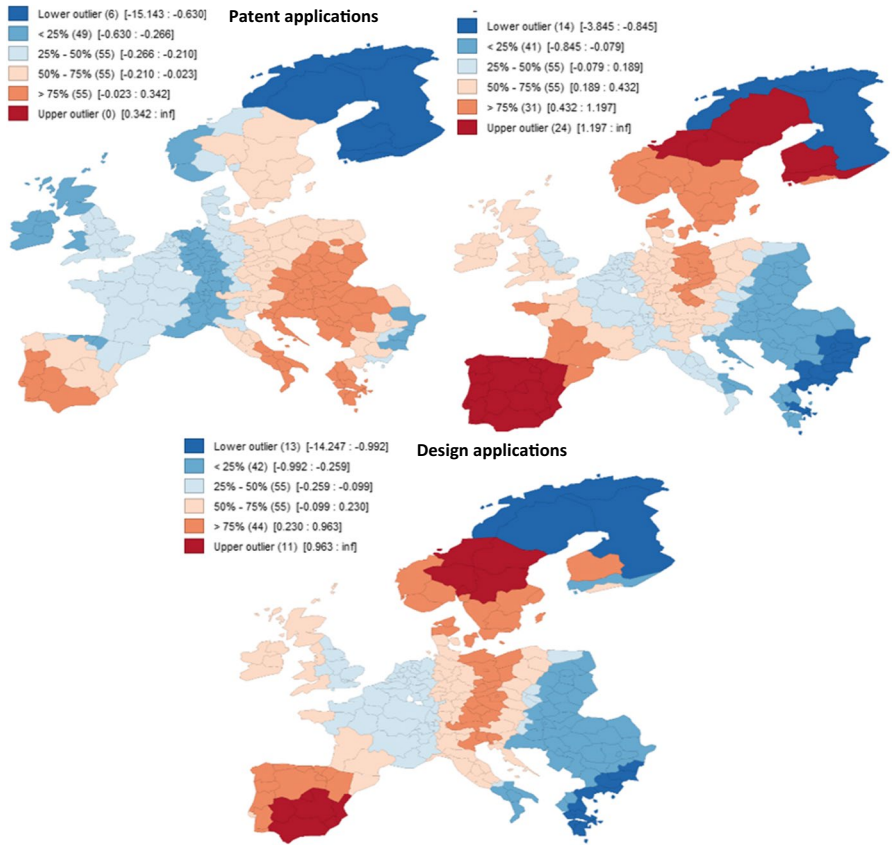


Fig. 12 Box maps of local parameter estimates - Density

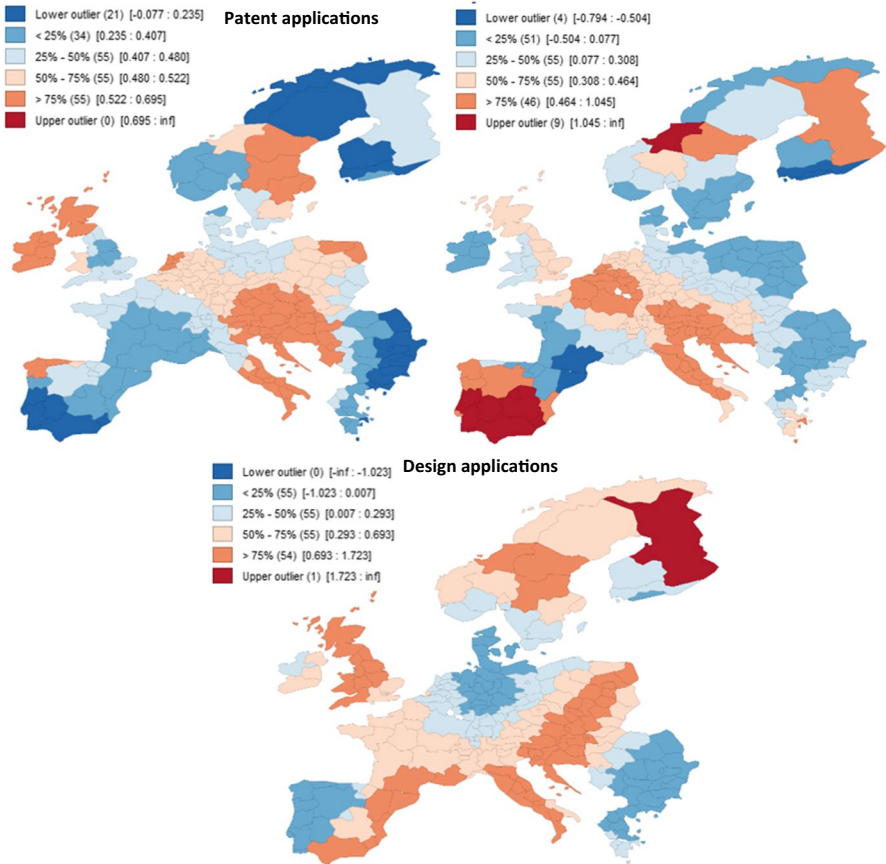


Fig. 13 Box maps of local parameter estimates – Spatial autoregressive parameter

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Data Availability The data are available on request from the author.

Declarations

Competing interests The authors declare no competing interests.

Disclosure The author declares no competing interests.

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