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Evaluating the spatial heterogeneity of innovation drivers: a comparison between GWR and GWPR

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Abstract
In studies focusing on innovation activities, the potential spatial heterogeneity in the relationships between innovation and its triggering factors is an unexplored topic. On this ground, this paper aims to a twofold contribution. First, we verify the existence of spatial variability in the relationships. We evaluate the estimation gains due to local regressions, such as geographically weighted regression (GWR) and geographically weighted panel regression (GWPR), with respect to the classical global methods (e.g., OLS, Fixed Effects panel regression). Second, we compare the GWPR with GWR and global models to evaluate if the joint consideration of time and space dimensions allows for the rise of new insights. We resort to official data on 287 NUTS-2 European regions in 2014–2021. The results confirm that GWPR estimations significantly differ from GWR and global models, potentially producing new patterns and findings.

Keywords Local regression models · GWR · GWPR · Panel · Innovation

1 Introduction

In the past few years, innovation has been gaining increasing attention and attracting the interest of scholars worldwide due to its prominent role as an engine driver for economic growth, dynamism, and competitiveness [3]. The growth of this interest and the awareness of the benefits of innovation processes have led to several European policies to encourage firms and territories to increase their innovation performance. For instance, in the early 2002s, European Union developed the 'Lisbon Strategy' proposing a multitude of guidelines to

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improve the Member States' economic development. Over a decade, the EU strategy to make the Union more competitive and dynamic was based on strengthening the knowledge-based economy, which is the foundation of good innovation performance [9]. There is no wonder many researchers have been working on identifying factors that influence or hinder innovation adoption by companies and territories. One of the starting points of previous research was investigating the relationship between the output side of innovation—which can be proxied by several variables such as patents or designs—and the more intuitive input side, namely research and development (R&D) expenditure. The R&D has empirically proved its fostering action in different periods and territories [27, 36]. Shefer and Frenkel [41], however, pointed out that the relationship between innovation and R&D is related, although to varying degrees, to different factors, such as firm size, organisational structure, ownership type, industrial branch, and geographical location. Their study revealed that large and central-located firms are inclined to invest more in R&D than the small and peripheral-located ones, thus emphasizing the spatially varying impact of R&D. There are many other drivers of innovation, with the empirical and theoretical literature ranging in interest from human capital [39], to workforce composition [32], to scientific collaborations [18]. A spatially varying relationship with innovation might be present for each of them. Despite the many contributions in literature, studies considering the territorial distribution of innovation determinants are still scarce. The relationship between innovation and its drivers presented in the most existing literature is essentially a global estimate, as the relationship applies invariantly over space. However, the expected relationship might differ in different territories since regions' development is uneven, and the time dimension deserves the proper attention within the same territory. Moreover, global estimates might be informative at a large spatial scale but misleading for regional development programmes since promoting regional development requires analysing regional disparities. Although there are studies considering the spatial dimension within the innovation-generating process, they lack an empirical framework to explore the hypothesis that the impact of its determinants may differ across territories. For example, the research performed by Moreno et al. [35] examined the spatial distribution of innovative activity in European regions, highlighting the key role played by R&D and agglomeration economies in local development. Ganau and Grandinetti [18] tested the role of innovation inputs from a regional heterogeneity perspective. The authors find that public and business R&D expenditure factors do not work unconditionally and everywhere. While the scholars aimed to analyse the spatial heterogeneity of innovation-enhancing factors, their work was based on an average relationship estimated through a Probit model.

To overcome this lack in spatial econometrics models, geographically weighted regression (GWR) was proposed [8], [16]. This local spatial approach allows constructing local models and estimating local regression coefficients. As the main advantage, GWR coefficients vary across the space, allowing to explore spatial heterogeneity explicitly. The GWR method has been previously used in empirical research concerning different application domains. The vast majority concern environmental issues to understand the spatial non-stationarity in factors influencing waste management [1, 2], soil quality and land use [31, 37], air quality [33, 34, 46], and, more in general, the management of resources [42, 45]. Several scholars have focused on security issues by investigating spatial heterogeneity in crime [28, 50] and traffic accident determinants [4, 24, 38]. They aimed to understand the factors that contribute to crime and crashes, intending to propose policies necessary for crime prevention, improve crash prediction and provide guidelines that could reduce their frequency or severity. Another group of scholars has applied this method to the empirical analysis of local socio-economic and environmental determinants of population growth and redistribution [19, 23, 49]. There is no shortage of works that considers local variations in the effects of hedonic attributes on housing prices, property values, and hotel room prices [11, 22, 43, 51] to set urban planning policy and building design and support decision–making processes. There are, however, still few applications of this exploratory technique in the field of innovation. Kang and Dall' Erba [26] have studied the spatially varying innovation capacity across U.S. MSA (metropolitan statistical area) and non-MSA counties and investigated each county's innovation strengths and weaknesses to suggest efficient place-tailored innovation policies. The analysis performed by Jang et al. [25] investigates spatially varying relationships between product innovation and sales performance to support the development of place-based product innovation strategies.

While GWR is a useful exploratory technique for studying phenomena where spatial non-stationarity is suspected, it suffers drawbacks, such as potential coefficients' multicollinearity [7]. Moreover, in the GWR, local models capture the geographic space information through cross-sectional data, not exploring the possibility that relationships are potentially varying also in temporal space. The first attempt to combine geographic space with temporal space was by Yu [52], who proposed geographically weighted panel regression (GWPR) by combining GWR with the panel data model. As the main methodological advancement, GWPR allows for studying local responses and detecting the presence of specific space-time patterns in the data. Unlike the widely used GWR technique, the more advanced GWPR method has few empirical research applications. The GWPR has found application in the environmental and transport system fields along with the GWR. Yu et al. [53] have assessed the relationships between access to high-speed rail system accessibility and the county's economic development in China to suggest new strategies for promoting relatively balanced regional development in China. As for the environmental applications, Li and Managi [30] have used the GWPR model to detect the local variation in the relationship between the air pollutant nitrogen dioxide and satellite-derived data to provide monitoring instruments and tools for air pollution control policies. This paper presents GWPR in the context of innovation studies seeking to contribute to the literature in two ways. First, to our best knowledge, this is the first research to examine how the relationships between innovation and its determinants vary locally. Therefore, for the first time, we study the spatiotemporally varying relationship between innovation and its determinants by combining GWR with the panel data model to detect the presence of specific space-time patterns in the data. Second, we evaluate whether new previously hidden insights in the dataset arise by considering the temporal space in local models. For this purpose, by resorting to innovation panel data from 2014 to 2021 for European regions (NUTS-2 of Eurostat classification), we compare the GWR results (estimated over several years) and GWPR estimations (on the whole period).

The article is structured as follows. In Sect. 2, we present the local models' framework and offer the methodological details. Section 3 presents the dataset used. In Sect. 4, the results for different models are compared and analysed. Section 5 concludes.

2 Methods: the path of spatio-temporal analysis

The linear regression model has always been one of the most useful methods to investigate the relationships among variables.

It takes the form:

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i; i = 1, \ldots, n, \tag{1}$$

where y_i and x_{ij} are, respectively, the response and the j-th explanatory variable for every unit in the sample $(i = 1,\ldots,n)$; k is the number of explanatory variables; β_0 is the intercept; β_j is the parameter estimate (coefficient) for the $j-th$ explanatory variable; and ε_i are independently and identically distributed error terms with expectation 0 and constant variance σ^2. Since the linear regression model is commonly estimated by Ordinary Least Squares (OLS), it is often labelled the OLS model.

This regression technique can, however, easily produce biased or inefficient estimations when the assumptions necessary for its implementation are no longer valid. Specifically, the dependency between nearby observations could break the assumption of uncorrelated residuals when dealing with spatial data. Spatial proximity influences the relationships between phenomena or objects: observations are related to one another, but closest observations are more related than those further away. Moreover, empirical evidence shows that the assumption of stationarity over space may be unrealistic since non-stationarity often concerns spatial data [16, 29]. So, the occurrence of spatial non-stationarity, i.e., the influence of explanatory variables on the dependent variable varies with the location of the observations, needs appropriate modelling strategies that take it into account [17]. Brunsdon et al. [8] have developed the Geographically Weighted Regression (GWR) model to fill this gap.

The GWR model is a local exploratory technique investigating the potential non-stationarity for relationships in a regression model in geographical space. It suits situations when the global (stationary) model does not properly describe spatial relationships and a localised fit is needed to address local variations. The model extends the OLS regression framework (1) by allowing local rather than global parameters to be estimated for each explanatory variable [15]. By repeating the estimation procedure at each point in space, GWR estimates as many coefficients as local areas, better reflecting the spatially varying relationships between dependent and explanatory variables. Moreover, this procedure provides a localised version of all standard regression diagnostics, including the goodness of fit.

Formally, the GWR model can be expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i; i = 1, \ldots, n, \tag{2}$$

where u_i, v_i are the geographical coordinates for each location i; y_i is the dependent variable at location i; x_{ij} is the $j-th$ independent variable at location i; k is the number of covariates; ε_i is the i.i.d. error term at location i. $\beta_0(u_i, v_i)$ and $\beta_j(u_i, v_i)$ denote the intercept and the $j - th$ regression parameter at the i-th location; both are a function of the geographical position.

The parameter vector at location$i$ is estimated by using the weighted least square approach as:

$$\widehat{\beta}(u_i, v_i) = \left(X^{'}W(u_i, v_i)X\right)^{-1}\left(X^{'}W(u_i, v_i)Y\right), \tag{3}$$

$W(u_i,v_i)$ is a $n \times n$ diagonal matrix denoting the geographical weighting of each observed data on the calibration of the model for point i. The weighting matrix changes for each location, ensuring that more proximal observations to the calibration location have a greater influence in estimating its regression parameters than those farther away.

A kernel function defines the weighting scheme. In this study, $W(u_i,v_i)$ is calculated with the bi-square kernel function, which assigns the observations a decreasing weight with distance, and this weight is zero above a specific distance (bandwidth) [7]:

$$w_{ij} = \left(1 - \left(\frac{d_{ij}}{h_i}\right)^2\right)^2 if d_{ij} < h_i, 0 \text{otherwise}, \tag{4}$$

where d_{ij} is the Euclidean distance between observations at locations i and j, while h_i is the bandwidth for the *i-th* location. The bandwidth is the key controlling parameter and can be specified by a fixed distance (fixed bandwidth), i.e., the bandwidth is the same at any point in the space, or by a fixed number of nearest neighbours (adaptive bandwidth), i.e., each unit has its bandwidth to ensure the same number of neighbours for all the regression points.

Yu [52] took another step forward in exploring spatial heterogeneity by combining GWR and panel data analysis. Geographically Weighted panel regression (GWRP) involves the time dimension in the GWR model assessing the time series of observations at a specific area as a realisation of a smooth spatio-temporal process [7]. Such a spatiotemporal process is based on the idea that closer observations, either in space or time, are more related than distant ones. This approach addresses two issues: (i) it takes the spatial structure of the data and non-stationary variables into account, extending the classical linear regression to local spatial models providing specific parameters for each local area,(ii) it also considers the time dimension, allowing more accurate results than the pooled models. The enlarged sample size gives more degrees of freedom and reduces the collinearity among explanatory variables, thus improving the efficiency of econometric estimates [48].

Following the procedure suggested by Yu [52], we keep on the analysis by performing the GWPR. A fixed or random effects model can be applied to obtain the spatially varying parameters. Since we resorted to the fixed effects model, we present this specification. For a set of locations indexed by i = 1, 2, …, n observed throughout the study period t = 1, 2, …, T, the GWPR with fixed effects can be written as [52]:

$$y_{it} = \beta_0(u_{it}, v_{it}) + \sum_{j=1}^{k} \beta_j(u_{it}, v_{it})x_{itj} + \varepsilon_{it}; i = 1, \ldots, n; t = 1, .., T, \tag{5}$$

where u_{it}, v_{it} are the geographical coordinates for the *i-th* location at time t; y_{it}, x_{itj}, and ε_{it} are, respectively, the dependent variable, the $j - th$ explanatory variable, and the error term at the *i-th* location at time t; k is the number of explanatory variables. $\beta_j(u_{it}, v_{it})$ is the coefficient of the $j - th$ variable for the *i-th* unit at time t, while $\beta_0(u_{it}, v_{it})$ is the intercept that denotes the time-invariant fixed effects. The Weighted Least Squares approach estimates the parameters in the GWPR model. Based on the same assumption of the GWR model that for each regression point (i), closer observations have more influence in estimating parameters than more remote observations, the weight system (W) is defined as a distance-decay function and is calculated with the bi-square kernel function using an adaptive bandwidth. As in the GWR case, also GWPR allows for fixed and adaptative bandwidth. The optimum bandwidth is determined by calibrating the GWPR model through the Cross-Validation (CV) criterion, which accounts for model prediction accuracy, defined as follows [52]:

$$CV = \sum_{i=1}^{n} \left(\overline{y}_i - \hat{\overline{y}}_{\neq i}(h_i)\right)^2 if d_{ij} < h_i, 0 \quad \text{otherwise}, \tag{6}$$

where $\overline{y}_i$ is the average over time of the dependent variable at the location i, $\hat{\overline{y}}_{\neq i}(h_i)$ is the fitted value of y_i with bandwidth h_i when calibrating the model with all the observations except y_i.

3 Data

The GWPR and GWR models are estimated on official data covering 2014–2021. The data are drawn from the 2021 edition of the Regional Innovation Scoreboard (RIS) by the European Commission (Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs).[1] RIS includes data on countries belonging to European Union or the European Free Trade Association (EFTA) but does not include data on EU candidate countries such as Turkey. As a result, this analysis covers 287 regions (NUTS-2 of Eurostat classification). Notably, resorting to NUTS-2 regions as the units of analysis allows using the finest territorial level for data availability.

The European Commission proposes the Regional Innovation Index (RII). The RII is a composite indicator calculated as the unweighted average of the scores of RIS variables. It combines the output side of innovation (e.g., the number of patent applications per billion GDP) and input variables (e.g., the R&D expenditure). Since the RII is a mixture of the innovation's input and output sides, it is unsuitable for regression analysis [12]. In this light, we split the RII's information into a composite indicator (the dependent variable) to capture the innovation capabilities of European regions and into a set of innovation drivers used as regressors. Notably, all RIS variables are normalised, ranging from 0 to 1.[2]

Based on the above, the dependent variable is a composite indicator obtained as the average of five elementary variables [21]. The elementary variables are listed in Table 1 (section 'Innovation Output'). The patent, trademark, and design variables measure the final or intermediate step of the innovation process due to large firms and/or service sectors [12]. The SMEs' innovation and Sales of new-to-market and new-to-firm innovations variables capture the innovation due to small and medium firms [12]. As well as the elementary variables, the dependent variable is normalised, ranging 0–1. We have controlled for a set of explanatory variables as suggested by the innovation-related empirical literature. The explanatory variables are listed in Table 1 (section 'Innovation Input'). Finally, Fig. 1 shows the territorial distribution of variables.

4 Empirical results

The paper focuses on the GWR extension to panel data and its differences with in-average models and cross-sectional GWR. We have estimated several models to emphasise the differences between global regressions (cross-section and panel) and local regressions. In particular, regarding the cross-section models, we present the global estimations for 2014, 2017, 2019, and 2021. The GWR models have been estimated for the same years. Notably, we report only these years for the sake of space, but we have estimated OLS and GWR models for each year in the 2014–2021 timespan. The results of the other cross-sectional models are available upon request. Regarding the panel models, we present the results of panel regression with fixed effects and GWPR with fixed effects in 2014–2021.

Table 2 shows the global models' cross-sectional and panel regression estimations. Regard-

[1] The data can be found at the following URL:https://research-and-innovation.ec.europa.eu/statistics/performance-indicators/regional-innovation-scoreboard_en.

[2] As stated by European Commission [13] the data are normalised using the min–max procedure. The minimum score observed for all regions is first subtracted from the regional score. The result is then divided by the difference between the maximum and minimum scores observed for all regions. Formally, the procedure is the following: $\frac{X_r - \min(\forall_r X_r)}{\max(\forall_r X_r) - \min(\forall_r X_r)}$

Table 1 Definition of variables

Variable	Definition	References
Innovation output		
Patent applications	Number of patents applied for at the EPO (by year of filing and inventor's address) per billion regional GDP in PPS	[6]
Trademark applications	Number of trademarks applied for at the EUIPO per billion regional GDP in PPS	[18]
Design applications	Number of designs applied for at the EUIPO per billion regional GDP in PPS	[21]
SMEs' innovation	Number of SMEs introducing a product, process, marketing or organisational innovation as a percentage of total SMEs	[32]
Sales of new-to-market and new-to-firm innovations	Sum of the total turnover of new or significantly improved products for SMEs as a percentage of SMEs' total turnover	[21]
Innovation Input		
Public R&D	Public expenditure dedicated to developing technological innovations and new products as a share of GDP	[35]
Business R&D	Expenditure in the business sector dedicated to developing technological innovations and new products as a share of GDP	[35]
Non-R&D innov. expenditure	Total innovation expenditure for SMEs as a percentage of SMEs' total turnover (excluding intramural and extramural R&D expenditures)	[21]
SME collab. innov	Number of SMEs with innovation co-operation activities (co-operation agreements on innovation activities with other enterprises or institutions) as a percentage of total SMEs	[32]
Education	Persons aged 30–34 years with some form of post-secondary education as a percentage of the total population aged 30–34 years	[39]
Lifelong learning	Persons in private households aged 25–64 years who have participated in the four weeks preceding the interview in any education or training as a percentage of the total population aged 25–64 years	[18]
Employment knowledge	Employed persons in knowledge-intensive services sectors as a percentage of the total workforce	[21]
Scientific research	Number of scientific publications among the top-10% most cited publications worldwide as a percentage of total scientific publications in the region	[18]

Fig. 1 Quantile maps of variables, 2014, 2017, 2019, and 2021. Note: **a** Public R&D; **b** Business R&D; **c** Non-R&D innovation expenditure; **d** SME collaborating for innovation; **e** Education; **f** Lifelong learning; **g** Employment knowledge; **h** Scientific research; **i** Innovation output

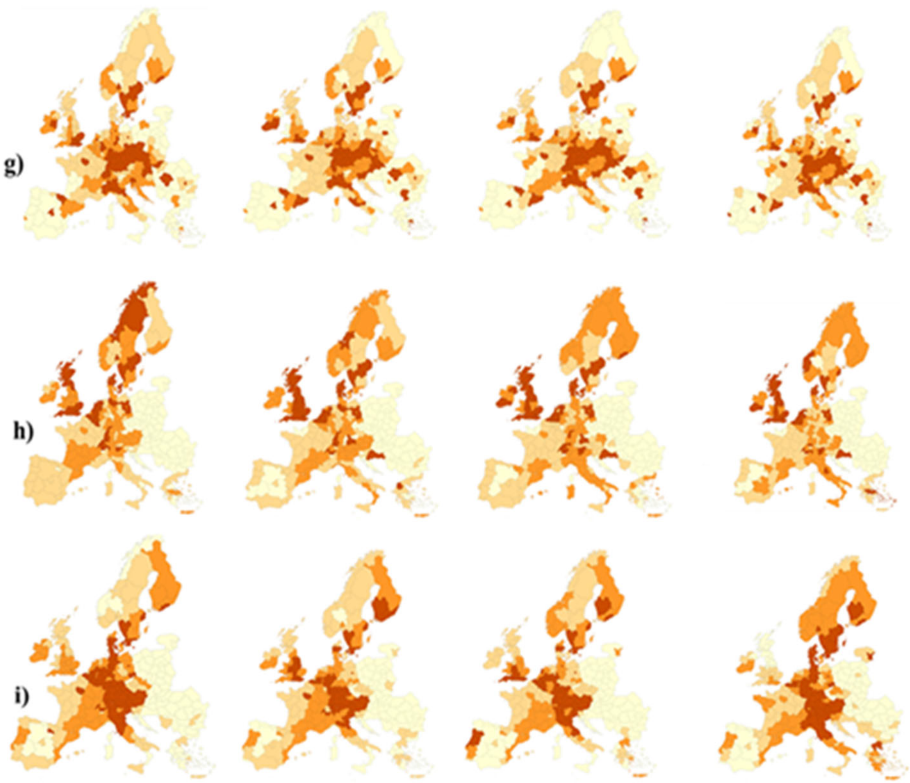

Fig. 1 continued

ing the results of the local regression, Table 3 shows the summary of coefficient estimates, while Fig. 2 shows the coefficients' territorial distribution by quantiles. Before focusing on the differences between the models in terms of the consistency of the estimates, it is advisable to check the consistency of our results with the economic literature on the determinants of innovation. Regarding cross-sectional estimates, a relatively higher innovation outcome is mainly associated with a higher endowment of business R&D expenditure, non-R&D expenditure for innovation, scientific research, and employee in knowledge-related sectors. In particular, the results confirm the pivotal role of investment in research and development. On the one side, the business R&D might be related to large firms' activities leading their innovation activities [35],on the other side, non-R&D investments—such as the acquisition of machinery, market research, or feasibility studies—are suitable in explaining innovation in smaller entrepreneurship where in-house R&D activities are lacking [5, 44]. Notably, public R&D is statistically significant only in the 2021 model. Scientific research is another main innovation-driving factor. According to De Rassenfosse and de la Potterie [10], an explanation might be that academic contributions could incorporate market-oriented initiatives overcoming the boundaries of classic scientific research. More surprising are the results of the education variable since the coefficients show a negative impact on innovation. Although the result might sound strange, other evidence exists on the negative effects of human capital on innovation. For example, Roper and Hewitt-Dundas [40] found this relationship relatively

Table 2 Global regression (2014, 2017, 2019, and 2021) and global panel regression (2014–2021)

Variable	2014 Coeff	2017 Coeff	2019 Coeff	2021 Coeff	Fixed effects Coeff
Intercept	0.162*** (0.023)	0.171*** (0.024)	0.193*** (0.024)	0.259*** (0.028)	0.286*** (0.021)
Public R&D	− 0.003 (0.028)	− 0.014 (0.025)	0.044 (0.027)	0.187*** (0.034)	0.012 (0.020)
Business R&D	0.183*** (0.029)	0.190*** (0.027)	0.249*** (0.029)	0.253*** (0.039)	0.041* (0.021)
Non-R&D innov. expenditure	0.121*** (0.037)	0.077** (0.038)	0.098*** (0.035)	0.079* (0.046)	0.010 (0.009)
SME collab. innov	0.001 (0.029)	0.042 (0.026)	0.046* (0.025)	0.044 (0.037)	0.184*** (0.008)
Education	− 0.091*** (0.028)	− 0.062** (0.027)	− 0.047 (0.029)	− 0.168*** (0.033)	0.029 (0.018)
Lifelong learning	− 0.004 (0.030)	0.073*** (0.027)	0.028 (0.029)	0.052 (0.034)	0.063** (0.029)
Employment knowledge	0.187*** (0.029)	0.113*** (0.029)	0.041 (0.030)	0.069* (0.038)	0.027 (0.017)
Scientific research	0.301*** (0.029)	0.260*** (0.032)	0.239*** (0.032)	0.087** (0.044)	0.054*** (0.013)
R^2_{Adjusted}	0.701	0.692	0.661	0.528	0.121
N	287	287	287	287	2,296
Breusch-Pagan LM test	–	–	–	–	4348.8 (*p-value*:0.00)
Hausman test	–	–	–	–	145.2 (*p-value*:0.00)

***; **; *: Significance level at 1%, 5%, 10%. Standard errors in brackets. Values for Monte Carlo test columns are p values

to process innovation activities. Ganau and Grandinetti [18] used a composite indicator (similar to that used in this analysis) to measure the innovation activities finding a negative value for the human capital's coefficient.

Regarding the panel data global model, we resort to a fixed-effects model following the result of the Hausmann test (see Table 2). Some interesting insights emerge since the estimation differs from the cross-sectional ones. First, only business R&D and scientific research remain statistically significant. The relevant role of the collaboration between SMEs and lifelong training programs emerges from introducing time dimensions. In particular, SMEs can use collaborative agreements to share know-how and exploit opportunities by interacting with similar agents [20]. However, knowledge sharing is time-consuming,this could explain why this variable becomes significant in the panel model. Similarly, lifelong learning programs need time to recalibrate and reskill the workforce to provide the technical competence and mastery of analytic tools that could stimulate creative thinking and facilitate its utilisation [5].

We estimate GWR and GWPR with fixed effects models to explore the coefficients' spatial heterogeneity. As a first step, we define the optimal kernel bandwidth by minimising the cross-validation (CV) criterion. The procedure suggests using the adaptative bi-square kernel with

Table 3 Summary of GWR and GWPR coefficient estimates and Monte Carlo test

	GWR 2014							
Variable	Min	Q1	Median	Q3	Max	Mean	St. Dev	Monte Carlo test
Intercept	− 0.029	0.098	0.239	0.411	0.563	0.258	0.176	0.00
Public R&D	− 0.129	− 0.064	− 0.018	0.026	0.152	− 0.008	0.072	0.38
Business R&D	− 0.028	0.049	0.093	0.162	0.231	0.102	0.063	0.47
Non-R&D innov. expenditure	− 0.064	0.076	0.100	0.130	0.226	0.101	0.057	0.97
SME collab. innov	− 0.110	− 0.009	0.046	0.184	0.459	0.097	0.148	0.00
Education	− 0.247	− 0.137	− 0.038	0.032	0.147	− 0.048	0.103	0.00
Lifelong learning	− 0.244	− 0.113	− 0.040	0.021	0.529	− 0.014	0.168	0.00
Employment knowledge	− 0.010	0.099	0.141	0.194	0.444	0.165	0.103	0.10
Scientific research	− 0.080	0.071	0.171	0.302	0.657	0.201	0.157	0.00
Local R^2	0.643	0.837	0.872	0.894	0.968	0.856	0.066	–
	GWR 2017							
Variable	Min	Q1	Median	Q3	Max	Mean	St. Dev	Monte Carlo test
Intercept	− 0.046	0.001	0.241	0.358	0.459	0.237	0.135	0.00
Public R&D	− 0.167	− 0.130	− 0.034	− 0.017	0.038	− 0.038	0.034	0.95
Business R&D	− 0.040	− 0.020	0.155	0.206	0.354	0.138	0.091	0.04
Non-R&D innov. expenditure	− 0.119	− 0.102	0.136	0.181	0.308	0.101	0.104	0.39
SME collab. innov	− 0.207	− 0.167	0.077	0.137	0.322	0.062	0.111	0.00
Education	− 0.213	− 0.186	− 0.031	0.034	0.112	− 0.034	0.078	0.12
Lifelong learning	− 0.124	− 0.106	0.038	0.074	0.415	0.051	0.099	0.00
Employment knowledge	− 0.063	− 0.049	0.112	0.232	0.352	0.131	0.112	0.13

Table 3 (continued)

Variable	GWR 2017 Min	Q1	Median	Q3	Max	Mean	St. Dev	Monte Carlo test
Scientific research	– 0.059	– 0.041	0.167	0.266	0.448	0.185	0.113	0.05
Local R^2	0.644	0.795	0.838	0.896	0.969	0.834	0.074	–

Variable	GWR 2019 Min	Q1	Median	Q3	Max	Mean	St. Dev	Monte Carlo test
Intercept	0.046	0.138	0.261	0 .383	0.536	0.269	0.141	0.00
Public R&D	– 0.160	– 0.066	– 0.028	0.053	0.167	– 0.003	0.082	0.11
Business R&D	– 0.026	0.126	0.148	0.191	0.255	0.154	0.053	0.78
Non-R&D innov. expenditure	– 0.101	0.014	0.057	0.090	0.439	0.065	0.097	0.37
SME collab. innov	– 0.105	0.039	0.114	0.191	0.367	0.111	0.117	0.00
Education	– 0.328	– 0.056	– 0.009	0.070	0.160	– 0.014	0.103	0.00
Lifelong learning	– 0.201	– 0.094	– 0.029	0.093	0.449	0.025	0.168	0.00
Employment knowledge	– 0.105	0.014	0 .073	0.162	0.271	0.088	0.093	0.15
Scientific research	– 0.128	0.070	0.170	0.282	0.394	0.164	0.135	0.00
Local R^2	0.493	0.777	0.828	0.871	0.968	0.823	0.075	–

Variable	GWR 2021 Min	Q1	Median	Q3	Max	Mean	St. Dev	Monte Carlo test
Intercept	– 0.082	0.087	0.264	0.480	0.721	0.289	0.233	0.00
Public R&D	– 0.146	– 0.051	0.007	0.135	0.420	0.055	0.147	0.00
Business R&D	– 0.006	0.101	0.141	0.180	0.315	0.145	0.065	0.90
Non-R&D innov. expenditure	– 0.162	0.007	0.114	0.171	0.393	0.092	0.120	0.31
SME collab. innov	– 0.431	– 0.033	0.104	0.212	0.416	0.074	0.187	0.00
Education	– 0.259	– 0.089	0.013	0.082	0.151	– 0.015	0.117	0.03

Table 3 (continued)

	GWR 2021							
Variable	Min	Q1	Median	Q3	Max	Mean	St. Dev	Monte Carlo test
Lifelong learning	– 0.450	– 0.106	0.049	0.209	0.481	0.041	0.240	0.00
Employment knowledge	– 0.160	– 0.023	0.132	0.229	0.337	0.108	0.139	0.02
Scientific research	– 0.574	0.033	0.161	0.286	0.517	0.113	0.240	0.00
Local R^2	0.455	0.820	0.850	0.892	0.957	0.846	0.069	–
	GWPR 2014—2021							
Variable	Min	Q1	Median	Q3	Max	Mean	St. Dev	Monte Carlo test
Intercept	–	–	–	–	–	–	–	–
Public R&D	– 0.115	– 0.026	0.022	0.061	0.269	0.031	0.075	–
Business R&D	– 0.099	0.020	0.056	0.083	0.160	0.049	0.048	–
Non-R&D innov. expenditure	– 0.104	– 0.020	0.048	0.081	0.169	0.032	0.069	–
SME collab. innov	– 0.004	0.098	0.131	0.197	0.297	0.143	0.077	–
Education	– 0.355	0.002	0.061	0.123	0.237	0.045	0.117	–
Lifelong learning	– 0.216	– 0.029	0.011	0.066	0.217	0.012	0.082	–
Employment knowledge	– 0.291	– 0.054	0.017	0.049	0.177	– 0.015	0.106	–
Scientific research	– 0.054	0.028	0.051	0.077	0.195	0.052	0.041	–
Local R^2	0.006	0.039	0.164	0.272	0.461	0.180	0.139	–

93 nearest neighbours.[3] The adaptive bandwidth is adopted to account for the density of the observations. The kernels will have larger bandwidths where the data are sparse and smaller bandwidths where the data are denser. Once the optimal kernel bandwidth is defined, we test

[3] Notably, for the five models (GWR 2014, 2017, 2019, and 2021, and GWPR) the optimal bandwidth procedure converges towards adaptative bi-square kernel but it highlights different nearest neighbours: 85 (GWR 2014), 58 (GWR 2017), 44 (GWR 2019), 62 (GWR 2021), and 93 (GWPR). This is not surprising since CV procedure is based on the value of dependent and independent variables. We adopt the larger bandwidth for sake of comparability between models. However, the estimations with different adaptative bi-square kernels show very similar patterns (respect to those reported in the paper). We do not report here for conciseness but are available upon request.

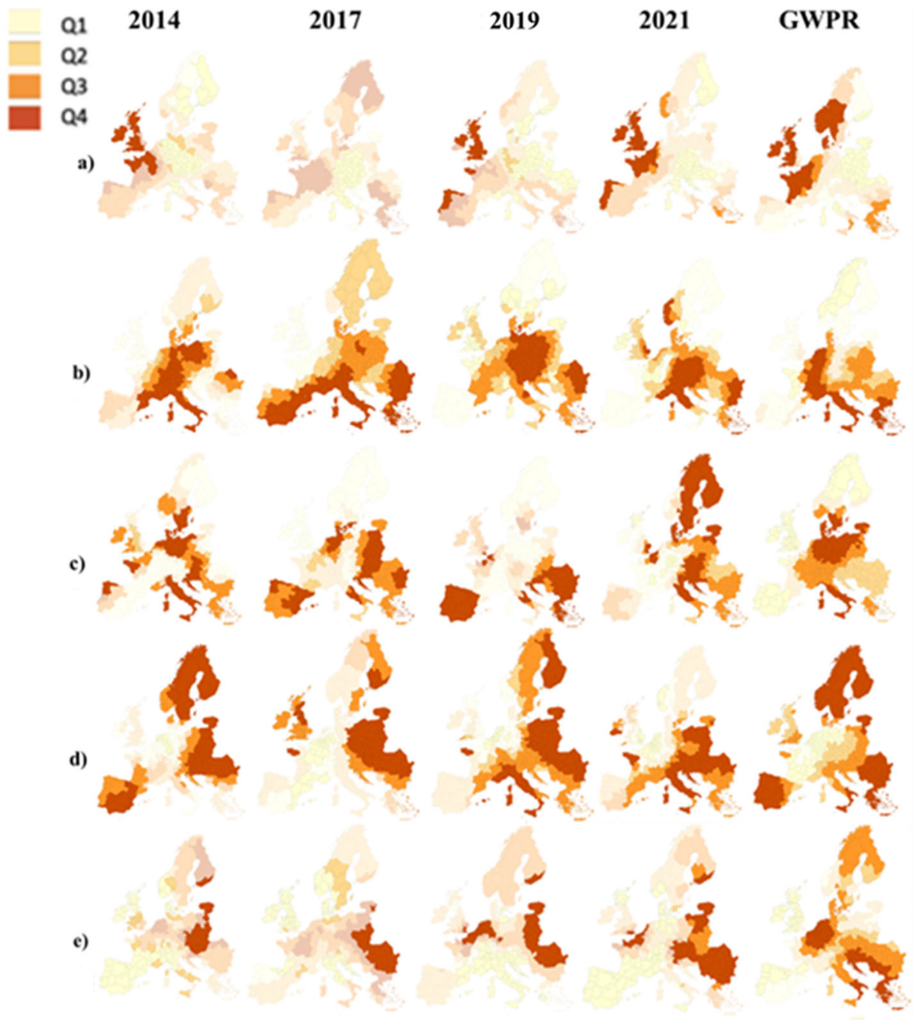

Fig. 2 Coefficients generated with GWR (2014, 2017, 2019, and 2021) and GWPR by quantiles. Note: **a** Public R&D; **b** Business R&D; **c** Non-R&D innovation expenditure; **d** SME collaborating for innovation; **e** Education; **f** Lifelong learning; **g** Employment knowledge; **h** Scientific research; **i** Local R^2_{adjusted}. The coefficients not statistically significant are shadowed

the spatial non-stationarity of parameters through the Monte Carlo significance test.[4] The results of the Monte Carlo test (Table 3) show that the associations between innovation and its determinants are deemed mostly non-stationary in European regions. Notably, exceptions exist. In particular, for 2014, the coefficients of the following variables are stationary: public and business R&D, non-R&D innovation expenditure, and employment in the knowledge sectors. In 2021 the scenario changed significantly since only Business R&D and non-R&D

[4] We estimate the GWR and GWPR models through R software. Unfortunately, the Monte Carlo test has not implemented in GWPR routine yet. For this test, we only refer to GWR. The spatial variability of GWPR local parameters can be evaluated only through the F test (at least one coefficient is spatially varying) and the local t tests.

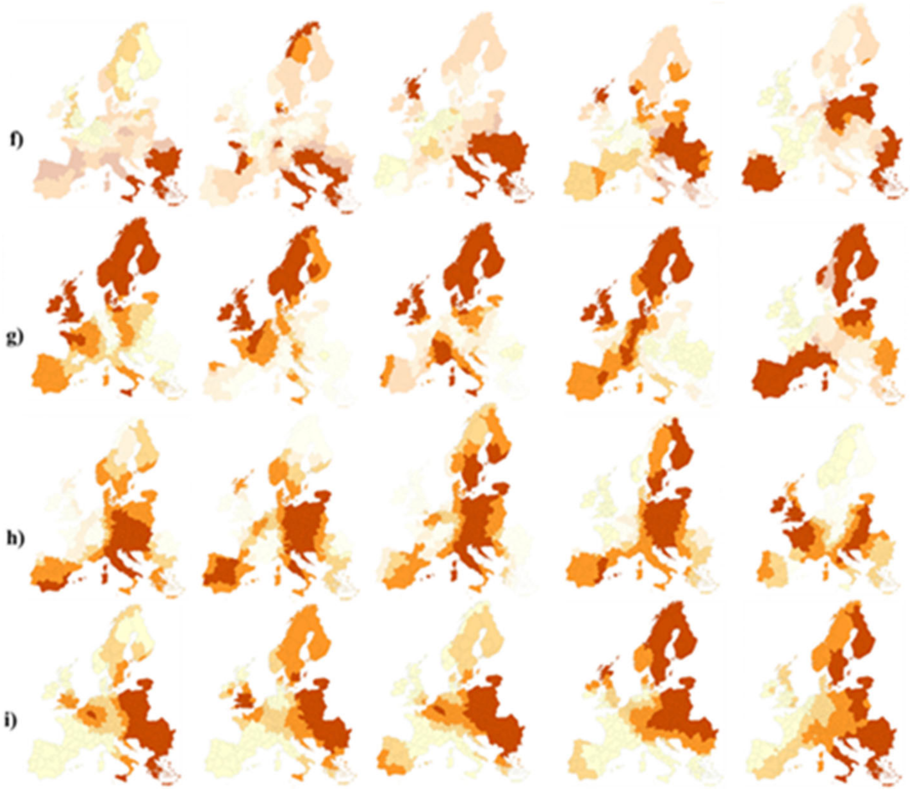

Fig. 2 continued

innovation expenditure failed the non-stationary test. On the one hand, this emphasises the need for local fitting techniques to improve estimates' accuracy and provide more suitable analysis. Conversely, a remarkable change in regional innovation determinants emerges over time. On this basis, it is clear how conducting a cross-sectional study would lead to a partial representation of the driving forces of innovation in European regions. Finally, we perform the Hausmann local tests to evaluate which panel estimation is more appropriate (random vs fixed effects) for GWPR. The results favour GWPR with fixed effects since we reject the null hypothesis in 245 out of 287 regions.

Figure 2(a–h) shows quantile maps of local cross-sectional coefficients and local fixed effects panel estimates. The coefficients not statistically significant are shadowed. Figure 2(i) shows the local adjusted R^2. Some interesting observations emerge. First, comparing GWPR and cross-sectional GWR models appears to be a general change in coefficients' quantile distribution and statistical significance. For example, public R&D is the only investment-related variable spatially varying (just in 2021), highlighting that regional-specific relationships do not exist with innovation activities. This consideration seems to change in the panel analysis since clear clusters of regions emerge. The regions of northern Europe (almost all of the UK and Ireland, many areas of France, Belgium, the Netherlands, Sweden and Norway) are characterised by a high impact of public R&D on innovation. The same occurs for Grecian regions. In east Europe and some Italian regions, the relationship is very weak. In all other regions, there is no effect. This result contrasts with previous works that pointed out the leading role of public R&D in average-based studies on the whole sample and research based on a regional split of European territory [18], [32]. This might be because the previous empirical analyses were conducted using average estimation methods within the identified sub-sample.

Local regressions show an even more noticeable improvement in estimates for collaborating SMEs for the innovation variable. While the coefficients are not significant in the global models, the local regression analyses prove the pivotal role of the SMEs' collaborating activities in enhancing the innovation performance of some regions. However, the full impact of collaboration emerges only in the GWPR model since the spatio-temporal patterns suggest the existence of relevant information hidden in local cross-sectional estimations. First, the GWPR leads to a considerable improvement in coefficients' statistical significance with respect to GWR. Second, GWPR highlights how it is a crucial driver in Mediterranean countries, east Europe, and the Scandinavian peninsula. This pattern does not arise in the GWR models (for example, the estimates fail to capture the role of the variable in Italy and Greece (2014) and Spain (2021)). However, this shall not come as a surprise considering that the flow of knowledge between enterprises requires time, and this feature is rather obscured in local cross-sectional analysis. Moreover, regional-specific characteristics emerge. For example, the Scandinavian and Greek regions feature a significantly higher SME collaboration performance than the whole EU, i.e., their regions dominate the list of the top 40 European best-performing regions [21]. Finally, the local estimations significantly improve the goodness of fit, especially in the GWPR case. Indeed, in GWPR, the values of local $R^2{}_{\text{adjusted}}$ ranging 0.007–0.461 (average = 0.181,median = 0.164; third quartile = 0.272), increasing respect to the 0.121 of the global model.

Figure 3 shows the differences in β coefficient estimates between local (GWR/GWPR) and global (OLS/FE panel) regressions. This figure shows to what extent the global effects of determinants deviate from the local ones. Quantities depicted in Fig. 3 are calculated by subtracting the absolute value of the local coefficient estimate from the absolute value of the global coefficient estimate of a given explanatory variable. A negative value (darker colour in Fig. 3) indicates that global regression overestimates the effect of the variable of concern compared to local regression. Conversely, a positive value (lighter colour in Fig. 3) refers to underestimation by the global model. We consider the coefficient not statistically significant in local regressions as not different from the global ones. They are shadowed in the figure. To clarify, the change in innovation output due to a unit change in any covariate is higher for the local model (compared to the global one) for European regions where global results in underestimation. This is because of local variations in the effect of determinants. What emerges in Fig. 3 is a widespread underestimation of β in global regressions. That is, global coefficients may be deemed inadequate at the local level. Regarding cross-sectional results, Non-R&D innovation expenditure, SME collaborating for innovation, education, lifelong learning, and scientific research seem to have a higher effect on innovation output in Central and Eastern European regions than the OLS estimations. Business R&D is one of the few variables overestimated in global models. Notably, looking at the time evolution of GWR models, some innovation drivers (such as SME collaborating for innovation, employment knowledge, and scientific research) were underestimated in 2014 but overestimated by OLS in 2021, especially in Western regions. In this light, we find confirmations of the informational gains allowed by the longitudinal analyses. A clear example is SMEs collaborating for innovation. We have already highlighted that the variable is statistically significant only in the global panel model. Moreover, the local regressions comparison shows a reverse scenario in GWPR with respect to the GWR case. On the one hand, the global panel regression overestimates the effect of the variable at the local level in almost half of the regions under study.

Fig. 3 Differences between local (GWR, GWPR) and global (OLS/FE) estimates. Note: **a** Public R&D; **b** Business R&D; **c** Non-R&D innovation expenditure; **d** SME collaborating for innovation; **e** Education; **f** Lifelong learning; **g** Employment knowledge; **h** Scientific research; **i** Local $R^2_{adjusted.}$ The coefficients not statistically significant are shadowed

This can be seen in Tables 2 and 3: FE estimate equal to 0.184 vs. GWPR mean equal to 0.143 and GWPR median equal to 0.197. On the other hand, according to GWR, there seem to be no local effects in many European regions, but this is just because cross-sectional data do not capture a time-requiring phenomenon as a collaboration between actors is. In fact, a significant difference in the territorial distribution of coefficients' statistical significance can be observed in each year analysed. This inconsistency is overcome through the use of local regressions with panel data. Another example is Business R&D, which is overestimated in global cross-sectional models but underestimated in FE regression (notably, the coefficient is statistically significant only at 10%) (Fig. 3). According to Tables 2 and 3: the FE estimate

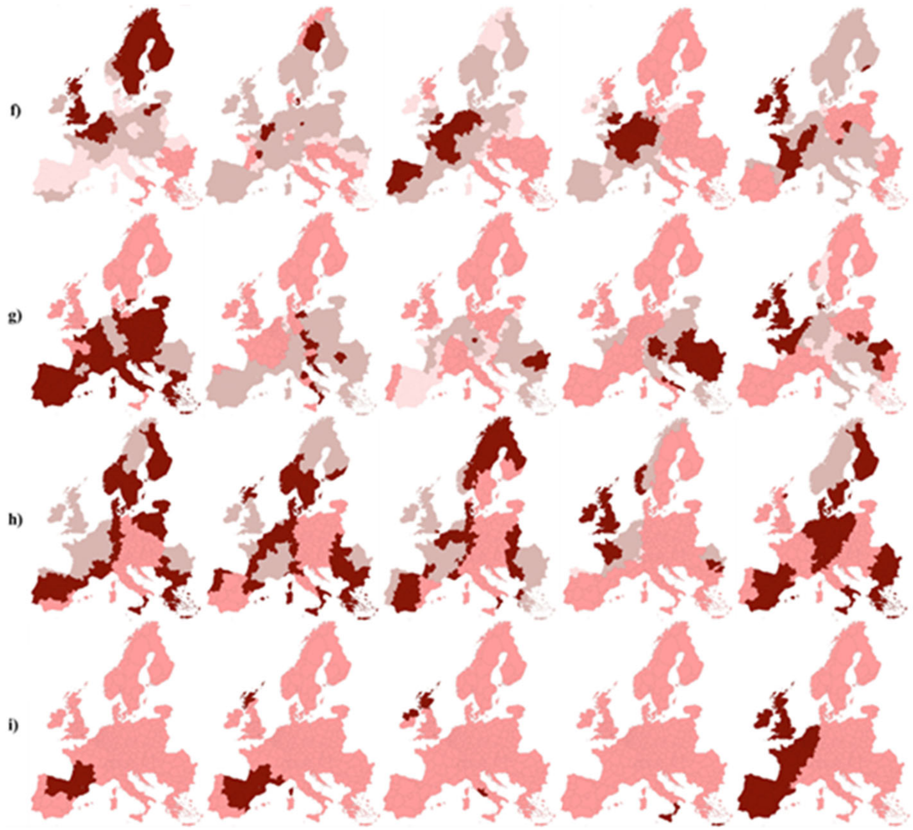

Fig. 3 continued

equals 0.041 *vs.* GWPR mean equal to 0.049 and GWPR median equal to 0.083. Also, in this case, the GWPR shows the gains of the local panel model with respect to cross-sectional ones for those drivers that require time to fully manifest their impact on another phenomenon. The goodness of fit, captured by $R^2_{adjusted}$, highlights an underestimation in global models. While in the GWR case, the local $R^2_{adjusted}$ are higher than the global one in almost all regions (some exceptions exist in the different years of GWR, in particular in some regions of Spain, France, and the UK), the GWPR shows an underestimation of global panel model in all regions except for Iberian peninsula, the UK and some regions of France or Belgium.

To compare the two local regression approaches (i.e., cross-sectional and panel), we report in Fig. 4 the coefficients' boxplot for GWPR and eight GWR models.[5] Box, whiskers (the vertical line in the plot), and dots refer to 25/75%, 10/90% and outliers of estimates, respectively. A general less variability of GWPR estimates emerges with respect to the GWR ones. This is especially true for those drivers—such as SMEs collaborating for innovation, or lifelong learning—that have shown the greatest benefits from the inclusion of the temporal component. In particular, the boxplot of SME collaborating for innovation variable suggests

[5] In Fig. 4 we show the results of all GWR estimated (one for each year in the period 2014–2021) and GWPR since the graphical representation allows it. For the other figures, as already stated, it is not possible for sake of space.

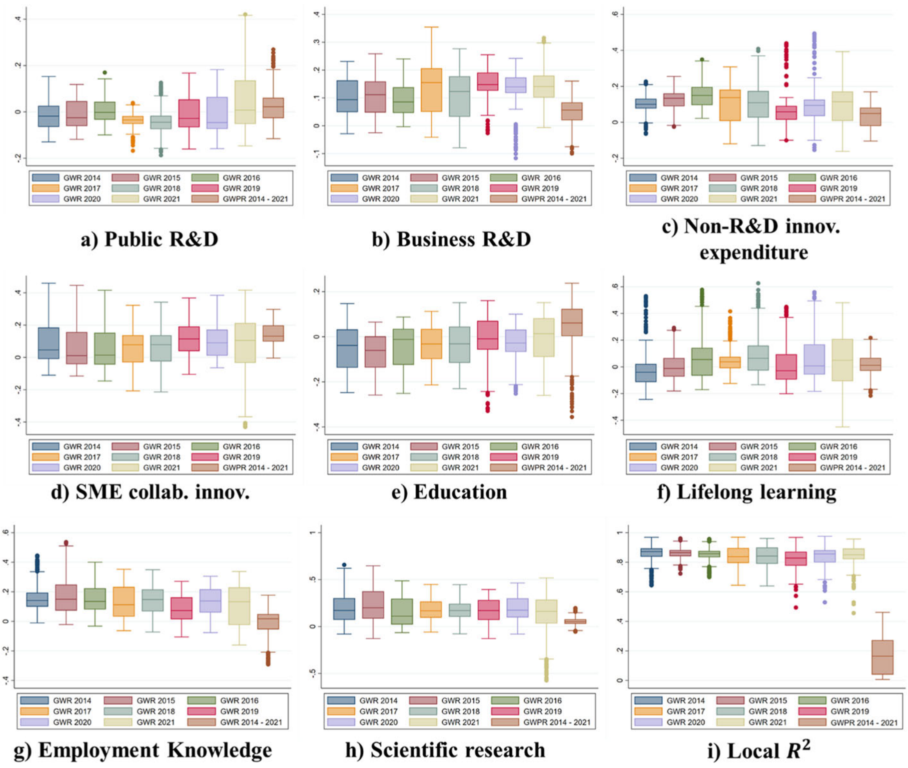

Fig. 4 Boxplot of GWR (2014–2021) and GWPR estimated coefficients

a symmetric distribution (just the median is nearest to the first quartile) and whiskers of equal length. In the case of GWR, conversely, the distribution is clearly asymmetric (right) except for GWR 2021 where it changes significantly, showing a marked negative asymmetry and some outliers. Other examples are lifelong learning and scientific research variables. Both show tighter boxes in GWPR with respect to GWRs. In the lifelong learning case, the time dimension reduces the occurrence of outliers in the right tail of distribution albeit showing some outliers in the left tail. Figure 4 also highlights the gain due to the GWPR estimation for the education variable since almost 75% of European regions present the expected positive relationship with innovation output. For GWRs, the scenario is reversed confirming the limits of cross-sectional data in capturing the time-requiring relations. Finally, the goodness of fit is more evenly distributed in the GWPR case, albeit it features positive asymmetry. In fact, the evolution of local R^2_{adjusted} in the cross-sectional case is characterized by high variability in the width of the boxes, left asymmetry, and a significant presence of outliers, especially in the left tail (GWRs in 2017 and 2018 are exceptions).

Figure 5 shows the parallel coordinate plots (PCPs). PCPs of estimated GWR and GWPR coefficients are visualizations used to compare variables to find patterns, similarities, clusters, relationships, and evaluate their spatial heterogeneity [47]. Each axis represents a covariate whose related coefficient gradually gets larger moving from the left to the right. The green lines in Fig. 5 correspond to the European regions. In general, we can interpret the plot in this way [14]: (i) wider ranges of coefficients imply greater spatial heterogeneity,(ii) parallel lines

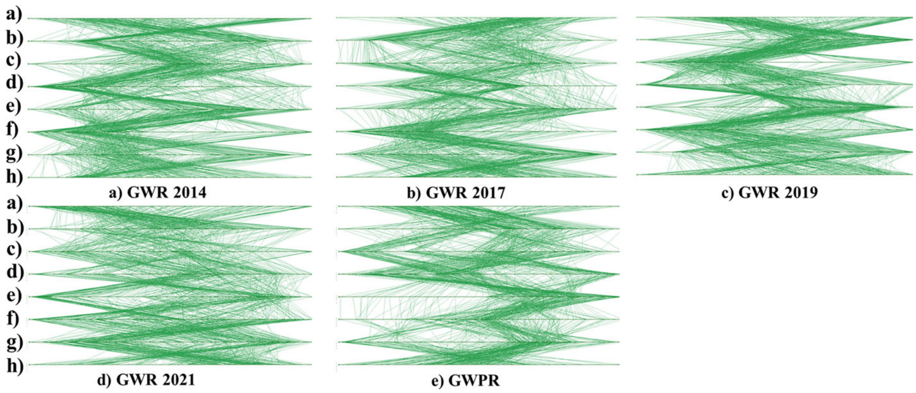

Fig. 5 Parallel coordinate plot of the estimated GWR and GWPR coefficients. Note: **a** Public R&D; **b** Business R&D; **c** Non-R&D innovation expenditure; **d** SME collaborating for innovation; **e** Education; **f** Lifelong learning; **g** Employment knowledge; **h** Scientific research

indicate a positive relationship between variables whilst crossing lines (X shapes) indicate a negative association. Figure 5 confirms point (i) for all local regressions, giving another proof of the appropriateness of local estimation to properly understand the innovation-generating process. In this view, Table 3 shows that the regression coefficients span a wide range, as proven by the min–max range and coefficients' standard deviation. In the comparison between GWR and GWPR interesting results emerge for knowledge-related variables, namely education, lifelong learning, and employment knowledge. Indeed, in GWPR, a pattern hidden in cross-sectional data suggests the synergic action of this variable in many regions.

In sum, determining the significant factors in innovation activities helps to understand the innovation-generating process and develop adequate policies and managerial actions. In this sense, local regressions arise as a better tool to capture the heterogeneity of factors' impact across regions (as well as the others level of territorial detail). Information obtained from local regressions can aid in the identification of regions in which similar factors are of greater importance. As a say, training programmes or particular policy actions could be addressed to specific clusters of regions. In this field, GWPR expands the advantages of GWR returning local coefficients featuring lesser variability, higher statistical significance and showing patterns and synergies among drivers otherwise hidden.

5 Conclusions

The aim of the work was twofold. First, it contributes to the growing literature on the innovation-generating process considering the spatial heterogeneity of its main determinants. To this end, we resort to local regressions, namely GWR and GWPR, to identify regions characterised by similar driving forces. This broadens the range of local policies to enhance innovation output. Second, the work presents the GWPR method as a procedure to fill the gap between GWR literature and panel data literature. The main originality of GWPR is that it allows studying potential spatial heterogeneity in models controlling for individual heterogeneity.

We focused on 287 European regions for 2014–2021. We proposed and compared different model specifications: (i) global cross-sectional regressions (2014, 2017, 2019 and 2021); (ii) global panel regressions with fixed effects in 2014–2021; (iii) GWR (2014, 2017, 2019, and 2021); (iv) GWPR in 2014–2021. Notably, the global and local cross-sectional models were estimated in each year of 2014–2021, but for space, we have reported only the results for the years mentioned above. Some interesting results emerge. The empirical analysis highlights new insights into local relationships. While the R&D-related variables, one of the most recognised innovation drivers, do not appear to exhibit marked and constant spatial variability, the collaboration between SMEs, the scientific research and the knowledge-related variables (i.e., education, lifelong learning, and employment knowledge) seem the engine of local innovation generating process. This is a key achievement since the global regressions seem to fail to capture the actual weight of these drivers. In other words, studying the innovation-generating process requires considering the spatial dimension by constructing local models since each territory has specific resources setup and development patterns. This seems particularly true for European regions, characterised by high diversified innovation factors framework.

Comparing GWPR with GWR, the local estimates are somewhat different when introducing the time dimension. SME collaborating for innovation is a clear example of the gains obtained jointly considering the space and time dimensions. In fact, its full impact on innovation emerges only in the GWPR model. As a say that strategies, collaboration agreements and investments do not produce immediate effects, but time is needed to evaluate the results on innovation performance. The GWPR also shows a clear cluster of regions (e.g., the Scandinavian peninsula, Greece, or Spain) where collaboration between SMEs is particularly important to trigger innovation activities. As a result of the analysis, we can highlight two strengths of GWPR. First, from a methodological point of view, GWPR expands the advantages of GWR returning local coefficients featuring lesser variability, higher statistical significance and showing patterns and synergies among drivers otherwise hidden. Second, from an economic point of view, GWPR allows performing an all-around analysis of innovation processes that helps understand regional-specific characteristics and intervention needs.

In light of the lack in the innovation literature of studies addressing spatial heterogeneity and the GWPR state of the art in the early stage, future contributes are needed. Future research developments might include the introduction of other potentially relevant regressors and finer spatial data (e.g., provincial level). Moreover, introducing a new option in the software routine may also allow evaluation of the spatial variability in GWPR (i.e., Monte Carlo simulation) and the local multicollinearity (i.e., local VIF).

Data availability statement The data that support the findings of this study are available from the corresponding author, GM, upon reasonable request.

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