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Evaluating the determinants of innovation from a spatio-temporal perspective. The GWPR approach

Una prospettiva spazio-temporale per lo studio delle determinanti dell'innovazione. L'approccio GWPR

Gaetano Musella, Giorgia Rivieccio, Emma Bruno

Abstract Innovation is one of the main leverages of regional economic development. It has been previously studied through classical methods (e.g., OLS) without considering the potential spatial heterogeneity influence. Local regression methods, such as geographically weighted regression (GWR), might describe the phenomenon more appropriately. The geographically weighted panel regression (GWPR) combines GWR with panel estimation controlling for spatial and individual heterogeneity as a methodological enhancement. This paper compares the estimates of GWPR, GWR and global models using 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.

Abstract L'innovazione è una delle principali leve dello sviluppo economico regionale. Gli studi precedenti hanno analizzato il fenomeno utilizzando modelli classici (ad esempio, OLS) senza considerare la potenziale influenza dell'eterogeneità spaziale. Il fenomeno potrebbe essere descritto in modo più appropriato dai metodi di regressione locale, come la geographically weighted regression (GWR). La geographically weighted panel regression (GWPR) rappresenta un avanzamento metodologico combinando la GWR con i modelli panel. Il presente lavoro confronta la GWPR con i modelli classici e con la GWR utilizzando dati su 287 regioni europee nel 2014-2021. L'analisi evidenzia come la GWPR produca risultati significativamente diversi dalla GWR e dai modelli globali.

Keywords: Local regression models, GWR, GWPR, Panel, Innovation

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1 Introduction

During the last years, innovation has claimed the interest of scholars around the world. Ahmad and Zheng (2022) highlighted the leading role played by innovation as an engine driver for economic growth, dynamism, and competitiveness. This interest has led to several European policies aimed to foster the innovation performance of firms and territories. For example, the European Union established in early 2002s the 'Lisbon Strategy' proposing a multitude of guidelines to improve the Member States' economic development. Enhancing the knowledge-based economy, a pillar of good innovation performance, was considered a cornerstone of the EU strategy to make the Union most competitive and dynamic over a decade (European Communities, 2009).

It is not surprising that many researchers have aimed to identify the factors that encourage or hinder companies or territories in developing and adopting innovations. 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 (Park, (2005); Kim et al., (2012)). However, Shefer and Frenkel (2005) highlighted that the innovation-R&D relationship is related, albeit with different degrees, to firm size, organisational structure, ownership type, industrial branch, and location. What emerged from their study is that large firms tend to invest more in R&D than the small ones, and the pivotal role of urban areas composition since R&D tends to be concentrated in large urban areas. In other words, there is a spatially varying impact of R&D since it plays a more significant role in creating innovation in central than peripheral areas. Many other drivers of innovation exist, with the empirical and theoretical literature that has ranged its interest from human capital (Rodríguez-Pose and Wilkie, (2019)), to the composition of the workforce (Lopes et al., (2021)), to scientific collaborations (Ganau and Grandinetti, (2021)). A spatially varying relationship with innovation might be present for each of them.

Studies considering the territorial distribution of innovation determinants are still scarce despite many contributions. The expected relationship might differ in different territories since regions' development is uneven, and within the same territory, the time dimension deserves the proper attention. In other words, 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. Such estimates might be informative at a large spatial scale but might be misleading for regional development programmes. Promoting regional development requires analysing the regional disparities. Studies considering the spatial dimension in the innovation generating process exist. However, they lack an empirical framework to explore the hypothesis that driving factors have a different impact on innovation performance in different territories. For example, Moreno et al. (2005) examined the spatial distribution of innovative activity in European regions. They pointed out the relevance of R&D and agglomeration economies for local development. Ganau and Grandinetti (2021) tested the role of innovation inputs in 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 (Brundson et al., (1996); Fotheringam et al., (1997)). 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. While GWR is a useful exploratory technique for studying phenomena where spatial non-stationarity is suspected, it suffers drawbacks, such as potential coefficients' multicollinearity (Bruna and Yu, (2013)). 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. A first attempt to combine geographic space with temporal space was by Yu (2010), who proposed geographically weighted panel regression (GWPR) by combining GWR with the panel data model. As the main methodological advancement, GWPR allows studying local responses and detecting the presence of specific space-time patterns in the data.

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. 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 an innovation panel data from 2014 to 2021 for European regions (NUTS-2 of Eurostat classification), we compare the GWR results (estimated on 2014 and 2021 data) and GWPR estimations (on the whole period).

This article is structured as follows. In Section 2, we present the local models' framework. Section 3 offers the methodological details, while Section 4 presents the dataset used. In Section 5, the results for different models are compared and analysed. Section 6 concludes.

2 The path of spatio-temporal analysis

The ordinary least square (OLS) regression has always been one of the most useful methods to investigate the relationships among variables. It can, however, easily produce biased or inefficient estimations when the assumptions necessary for its implementation are no longer valid. Specifically, when dealing with spatial data, the dependency between nearby observations could break the assumption of uncorrelated residuals. The 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 (Fotheringham et al., (1997); Leung et al., (2000)). 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 modelling strategies that take it into account (Fotheringham et al., (2003)).

Geographically Weighted Regression (GWR) is a local exploratory technique investigating heterogeneity in data relationships across space. It suits situations when the global (stationary) model does not properly describe spatial relationships and a localised fit is needed. The model, pioneered by Brunsdon et al. (1996), extends the OLS regression framework by allowing local rather than global parameters to be estimated for each relationship in the model. By repeating the estimation procedure at each point in space, GWR estimates as many coefficients as local areas, thereby better reflecting the spatially varying relationships between dependent and explanatory variables.

Yu (2010) 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 (Bruna and Yu, (2013)). 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 for 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 (Wooldridge, (2002)).

3 Methodology

This paper investigates the determinants of innovation and the spatial non-stationarity of relationships across European regions. Following the procedure suggested by Yu (2010), we perform the analysis by using 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 (Yu, (2010)):

$$y_{it} = \beta_0(u_{it}, v_{it}) + \sum_{k=1}^{p} \beta_k(u_{it}, v_{it})x_{itk} + \varepsilon_{it}; \quad i = 1,2,\dots,N; t = 1,2,\dots,T \qquad (1)$$

where u_{it}, v_{it} are the geographical coordinates for the *i-th* location at time t; y_{it}, x_{itk}, and ε_{it} are, respectively, the dependent variable, the *k-th* explanatory variable, and the error term at the *i-th* location; p is the number of explanatory variables. $\beta_k(u_{it}, v_{it})$ is the coefficient of the *k-th* variable for the *i-th* unit, 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 assumption 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 function of the distance. More specifically, W 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) (Bruna and Yu, (2013)):

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

where d_{ij} is the Euclidean distance between observations at locations i and j, while h_i is the adaptive bandwidth for the *i-th* location: each unit has its proper bandwidth selected so that the same number of neighbours is considered for all the regression points. The optimum bandwidth is defined by calibrating the GWPR model through the Cross-Validation (CV) criterion, which accounts for model prediction accuracy, defined as follows (Yu, (2010)):

$$CV = \sum_{i=1}^{n} \left(\bar{y}_i - \hat{\bar{y}}_{\neq i}(h_i)\right)^2 \tag{3}$$

where $\bar{y}_i$ is the average over time of the dependent variable at the location i, $\hat{\bar{y}}_{\neq i}(h_i)$ 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 units of analysis are 287 regions of Europe. We have excluded the regions presenting missing data from the analysis. The European regions (NUTS-2 of Eurostat classification) as the units of analysis represent the finest territorial level for data availability. The regional 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).

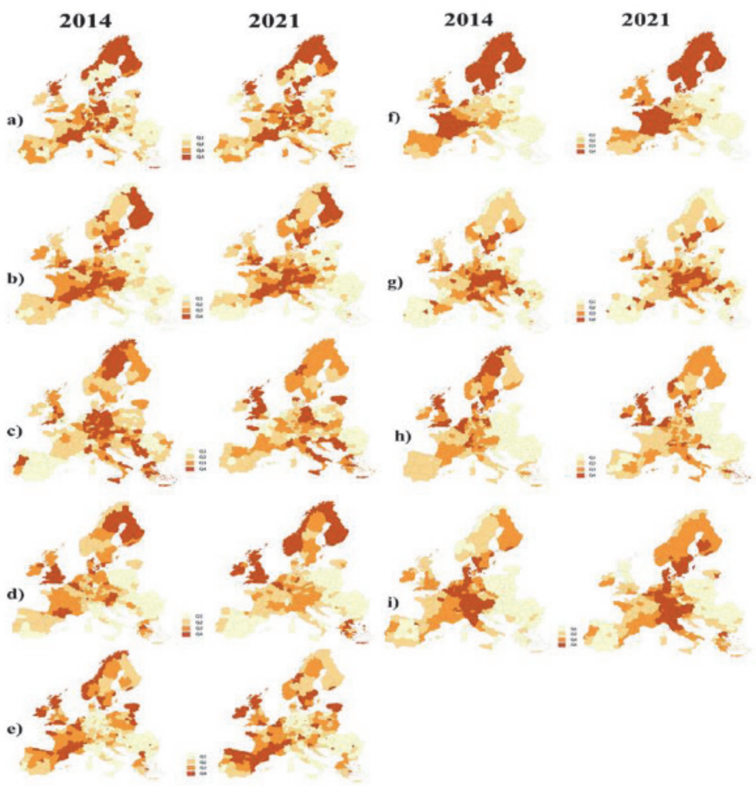
Moreover, The European Commission proposes the Regional Innovation Index (RII). The RII is a composite indicator calculated as the unweighted average of the scores of RIS variables. It combines the output side of innovation (e.g., the number of patent applications per billion GDP) and input variables (e.g., the R&D expenditure). Since the RII is a mixture of innovation's input and output side, it is not suitable for regression analysis (Edquist et al., (2018)). 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.

Based on the above, the dependent variable is a composite indicator obtained as the average of five elementary variables (Hollanders et al., (2019)). 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 (Edquist et al., (2018)). The SMEs' innovation and Sales of new-to-market and new-to-firm innovations variables capture the innovation due to small and medium firms (Edquist et al., (2018)). As well as the elementary variables, the dependent variable is normalised, and it ranges 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, **Figure 1** shows the territorial distribution of variables.

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	Braunerhjelm et al., (2020))
Trademark Applications	Number of trademarks applied for at the EUIPO per billion regional GDP in PPS	Ganau and Grandinetti, (2021)
Design Applications	Number of designs applied for at the EUIPO per billion regional GDP in PPS	Hollanders et al., (2019)
SMEs' innovation	Number of SMEs introducing a product, process, marketing or organisational innovation as a percentage of total SMEs	Lopes et al., (2021)
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	Hollanders et al., (2019)
Innovation Input		
Public R&D	Public expenditure dedicated to developing technological innovations and new products as a share of GDP	Moreno et al., (2005)
Business R&D	Expenditure in the business sector dedicated to developing technological innovations and new products as a share of GDP	Moreno et al., (2005)
Non-R&D innov. expenditure	Total innovation expenditure for SMEs as a percentage of SMEs' total turnover (excluding intramural and extramural R&D expenditures)	Hollanders et al. (2019),
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	Lopes et al., (2021)
Education	Persons aged 30–34 years with some form of post-secondary education as a percentage of the total population aged 30–34 years	Rodríguez-Pose and Wilkie, (2019)
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	Ganau and Grandinetti, (2021)
Employment knowledge	Employed persons in knowledge-intensive services sectors as a percentage of the total workforce	Hollanders et al. (2019),
Scientific research	Number of scientific publications among the top-10% most cited publications worldwide as a percentage of total scientific publications in the region	Ganau and Grandinetti, (2021)

Figure 1: Quantile maps of variables, 2014 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

4 Empirical results

The paper focuses on the GWR extension to panel data and its differences with in-average models and cross-sectional GWR. To emphasise the differences between global regressions (cross-section and panel) and local regressions, we present the results of several models, namely cross-section in 2014 and 2021, panel data with fixed effects, GWR in 2014 and 2021, and GWPR with fixed effects in 2014-2021.

Table 2 shows the global models' estimations. 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 (Moreno et al., (2005)); 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 (Thomä and Zimmermann, (2020); Baumol, (2005)). 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 (2009), 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 (2015) found this relationship relatively to process innovation activities. Ganau and Grandinetti (2021) 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 (Hervás-Oliver et al., (2021)). 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 (Baumol, (2005)).

Table 2: Global regression and Monte Carlo test (2014; 2021), global panel regression (2014-2021)

	2014		***2021***		***Fixed effects***
Variable	***Coeff.***	***Monte Carlo test***	***Coeff.***	***Monte Carlo test***	***Coeff.***
Intercept	0.162^{***} (0.023)	0.00	$.259^{***}$ (0.028)	0.00	0.286^{***} (0.021)
Public R&D	-0.003 (0.028)	0.38	0.187^{***} (0.034)	0.00	0.012 (0.020)
Business R&D	0.183^{***} (0.029)	0.47	0.253^{***} (0.039)	0.90	0.041^{*} (0.021)
Non-R&D innov. expenditure	0.121^{***} (0.037)	0.97	0.079^{*} (0.046)	0.31	0.010 (0.009)
SME collab. innov.	0.001 (0.029)	0.00	0.044 (0.037)	0.00	0.184^{***} (0.008)
Education	-0.091^{***} (0.028)	0.00	-0.168^{***} (0.033)	0.03	0.029 (0.018)
Lifelong learning	-0.004 (0.030)	0.00	0.052 (0.034)	0.00	0.063^{**} (0.029)
Employment knowledge	0.187^{***} (0.029)	0.10	0.069^{*} (0.038)	0.02	0.027 (0.017)

Scientific research	0.301^{***} (0.029)	0.00	0.087^{**} (0.044)	0.00	0.054^{***} (0.013)
R^2 Adjusted	0.701		0.528		0.121
N	287		287		2,296
Breusch-Pagan LM test	-		-		4,348.8 (*p-value*:0.00)
Hausman test	-		-		145.2 (*p-value*:0.00)

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

To explore the coefficients' spatial heterogeneity, we estimate GWR (for 2014 and 2021) and GWPR with fixed effects models. 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 93 nearest neighbours[1]. Once the optimal kernel bandwidth is defined, we test the spatial non-stationarity of parameters through the Monte Carlo significance test[2]. The results of the Monte Carlo test (**Table 2**) 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 knowledge sectors. In 2021 the scenario changed significantly since only Business R&D and non-R&D 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; on the other hand, a remarkable change in regional innovation determinants over time emerges. 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 a general

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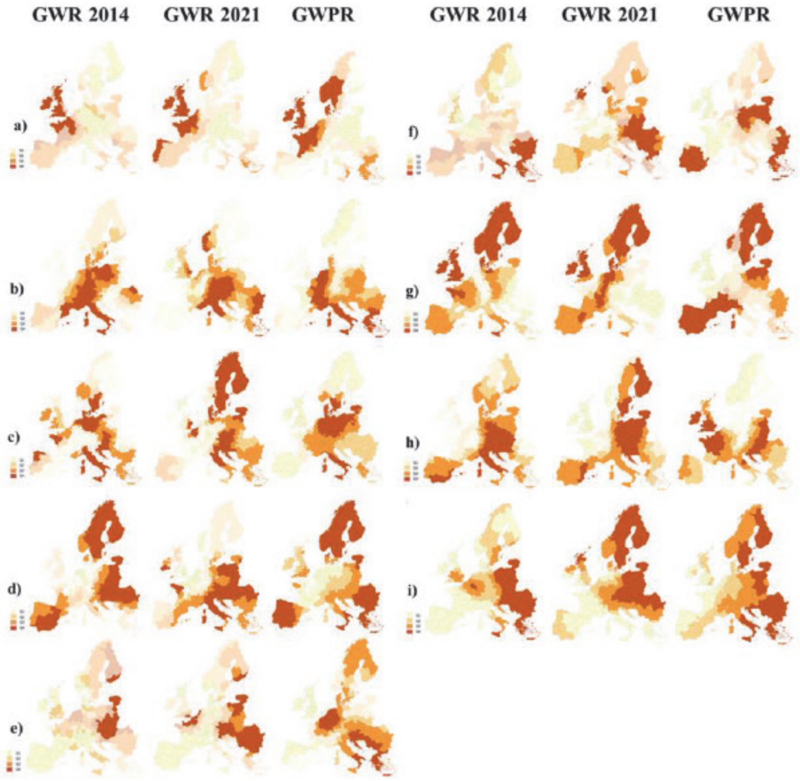
[1] Notably, for the three models (GWR 2014 and 2021, and GWPR) the optimal bandwidth procedure converges towards adaptative bi-square kernel but it highlights three different nearest neighbours: 85 (GWR 2014), 62 (GWR 2021), and 93 (GWPR). This is not surprising since CV procedure is based on the value 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.

[2] 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.

change in coefficients' quantile distribution and statistical significance. For example, the 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 is in contrast with previous works that pointed out the leading role of public R&D not only in average-based studies on the whole sample but also in research based on a regional split of European territory (Ganau and Grandinetti, (2021); Lopes et al., (2021)). This might be because the previous empirical analyses were conducted through average estimation methods within the sub-sample identified.

Local regressions show 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' significativity 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 (Hollanders et al., (2019)). Finally, the local estimations significantly improve the goodness of fit, especially in the GWPR case. Indeed, in GWPR, the values of local $R^2_{adjusted}$ 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 2: Coefficients generated with GWR (2014 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.

5 Conclusions

This work presents the GWPR method as a procedure able 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 compared the GWPR with global regressions (2014, 2021, and 2014-2021) and cross-sectional GWR (2014, and 2021). Some interesting results emerge. First, the local estimations accurately describe the relationship between innovation and its determinants regarding the global average models. Second, the local estimates are somewhat different when introducing the time dimension. Third, GWPR leads to an improvement in coefficients' statistical significance.

From an empirical point of view, 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 evaluating the spatial variability in GWPR (i.e., Monte Carlo simulation) and the local multicollinearity (i.e., local VIF).

References

1. Ahmad, M., Zheng, J.: The Cyclical and Nonlinear Impact of R&D and Innovation Activities on Economic Growth in OECD Economies: a New Perspective. Journal of the Knowledge Economy, 1-50. (2022).
2. Baumol, W. J.: Education for innovation: Entrepreneurial breakthroughs versus corporate incremental improvements. Innovation policy and the economy 5: 33-56 (2005).
3. Braunerhjelm, P., Ding, D., Thulin, P.: Labour market mobility, knowledge diffusion and innovation. European Economic Review 123, 103386. (2020).
4. Bruna, F., and Yu, D.: Geographically weighted panel regression. XI Congreso Galego de Estatística e Investigación de Operacións. http://xisgapeio. udc. es. (2013).
5. Brunsdon, C., Fotheringham, A. S., Charlton, M. E.: Geographically weighted regression: a method for exploring spatial non-stationarity. Geographical analysis, 28(4), 281-298. (1996).
6. Commission of the European Communities: Communication From the Commission to the Council, the European Parliament, the European Economic and Social Committee, and the Committee of the Regions: A Mid-Term Assessment of Implementing the EC Biodiversity Action Plan. Journal of International Wildlife Law & Policy, 12(1-2), 108-120. (2009).
7. De Rassenfosse, G., de la Potterie, B. V. P.: A policy insight into the R&D–patent relationship. Research Policy 38.5: 779-792 (2009).
8. Edquist, C., Zabala-Iturriagagoitia, J. M., Barbero, J., Zofío, J. L.: On the meaning of innovation performance: Is the synthetic indicator of the Innovation Union Scoreboard flawed?. Research Evaluation, 27(3), 196-211. (2018).
9. Fotheringham, A. S., Brunsdon, C., Charlton, M.: Geographically weighted regression: the analysis of spatially varying relationships. John Wiley & Sons. (2003).
10. Fotheringham, A. S., Charlton, M.E., Brunsdon, C.: Measuring spatial variations in relationships with geographically weighted regression. Recent developments in spatial analysis. Springer, Berlin, Heidelberg, 60-82 (1997).
11. Ganau, R., Grandinetti, R.: Disentangling regional innovation capability: what really matters?. Industry and Innovation, 28(6), 749-772. (2021).
12. Hervás-Oliver, J. L., Parrilli, M. D., Rodríguez-Pose, A., Sempere-Ripoll, F.: The drivers of SME innovation in the regions of the EU. Research Policy 50.9: 104316 (2021)
13. Hollanders, H., Es-Sadki, N., Merkelbach, I.: Regional innovation scoreboard 2019. (2019).
14. Kim, Y. K., Lee, K., Park, W. G., Choo, K.: Appropriate intellectual property protection and economic growth in countries at different levels of development. Research policy, 41(2), 358-375. (2012).
15. Leung, Y., Mei, C. L., Zhang, W. X.: Statistical tests for spatial non-stationarity based on the geographically weighted regression model." Environment and Planning A 32.1, 9-32 (2000).
16. Lopes, J. M., Silveira, P., Farinha, L., Oliveira, M., Oliveira, J.: Analyzing the root of regional innovation performance in the European territory. International Journal of Innovation Science. (2021).
17. Moreno, R., Paci, R., Usai, S.: Spatial spillovers and innovation activity in European regions. Environment and planning A, 37(10), 1793-1812. (2005).
18. Park, W. G.: Do intellectual property rights stimulate R&D and productivity growth? Evidence from cross-national and manufacturing industries data. Intellectual Property and Innovation in the Knowledge-Based Economy, Industry Canada, Ottawa, 9, 1-9. (2005).
19. Rodríguez-Pose, A., Wilkie, C.: Innovating in less developed regions: What drives patenting in the lagging regions of Europe and North America. Growth and Change, 50(1), 4-37. (2019).
20. Roper, S., Hewitt-Dundas, N.: Knowledge stocks, knowledge flows and innovation: Evidence from matched patents and innovation panel data. Research Policy, 44(7), 1327-1340. (2015).
21. Shefer, D., Frenkel, A.: R&D, firm size and innovation: an empirical analysis. Technovation, 25(1), 25-32. (2005).
22. Thomä, J., Zimmermann, V.: Interactive learning—The key to innovation in non-R&D-intensive SMEs? A cluster analysis approach. Journal of Small Business Management 58.4 :747-776 (2020)
23. Wooldridge, J. M.: Econometric analysis of cross section and panel data MIT press. Cambridge, MA 108.2, 245-254 (2002).
24. Yu, D.: Exploring spatiotemporally varying regressed relationships: the geographically weighted panel regression analysis. The international archives of the photogrammetry, remote sensing and spatial information sciences, 38(Part II), 134-139. (2010).