Economic Modelling 151 (2025) 107139

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Spatial regimes in heterogeneous territories: The efficiency of local public spending

Francesco Vidoli [a,*], Agnese Sacchi [a], Edgar J. Sanchez Carrera [b,1]

[a] Department of Economics, Society, Politics. University of Urbino Carlo Bo, Italy
[b] Department of Economics and Management (DISEI), University of Florence, Italy

ARTICLE INFO

Dataset link: https://data.mendeley.com/datasets/5nrk9f3p24/1

JEL classification:
C21
H72
O18
R12

Keywords:
Spatial regimes
Quantile regression
Unobserved heterogeneity
Urban traffic services
Local public spending

ABSTRACT

We study the impact of spatial heterogeneity on cost efficiency in Italian municipalities, introducing an original method to identify functionally homogeneous territorial areas that differ from existing administrative boundaries. Our method incorporates territorial and geographical dimensions, including latent variables associated with spatial heterogeneity—relevant factors yet often overlooked in previous empirical studies. Using spatial data on road and territory planning services, we identify clusters of municipalities with shared characteristics and measure their relative efficiency within these clusters. Our findings reveal marked territorial disparities in cost efficiency, challenging conventional one-against-all benchmarking methods. Unlike standard approaches that compare each municipality with all others, our method offers a more accurate basis for evaluating municipal performance and informing policy decisions on services to citizens. This contributes to a more effective and equitable allocation of public resources, addressing practical and methodological limitations in the existing literature.

1. Introduction

The economic literature has investigated the association between local spending efficiency and decentralised settings, mainly in advanced economies, using different empirical approaches and econometric techniques (Afonso and Fernandes, 2006; Geys, 2006; Balaguer-Coll et al., 2010; Goel et al., 2017; Choudhury and Sahu, 2023; Bucci et al., 2024; Afonso et al., 2024). The importance of spatial heterogeneity has been neglected in this context. In particular, the heterogeneity of the territorial communities served by local governments is relevant when allocating and efficiently spending public resources.

Local governments face socioeconomic and geographical heterogeneities when implementing public policies (Rey and Janikas, 2005), which might also be interdependent and affected by the neighbouring local governments' actions (Bordignon et al., 2003; Revelli, 2006). A persistent or even increasing misalignment between *administrative* and *socioeconomic* boundaries might emerge (Gaigné et al., 2016; Moreno-Monroy et al., 2021; Egan and Brander, 2022), thus influencing the outcome of local public provision to residents. Moreover, from a methodological point of view, latent or omitted variables related to the territorial context, which complement the administrative jurisdictional dimension, might represent a critical issue that possibly biases the empirical results (Vidoli and Fusco, 2018).

This paper aims to fill this gap by considering local territories' spatial heterogeneity and proposing an original method to identify territorial divisions that may be different from existing administrative boundaries (*e.g.*, regions, macro-regions) and maximise the degree of homogeneity of those areas for a specific quantile regressive function. Our methodological contribution consists of proposing an algorithm that can go beyond the local public finance framework and be applied to the more general interactions between economic agents when the often unrealistic assumption of spatial stationarity of functional relationships is discarded (Ciccarelli and Elhorst, 2018; Yang and Bradley, 2021; Egan and Brander, 2022).[2]

* Corresponding author.
E-mail addresses: francesco.vidoli@uniurb.it (F. Vidoli), agnese.sacchi@uniurb.it (A. Sacchi), edgar.sanchez@unifi.it (E.J.S. Carrera).

[1] Research Fellow at the Applied Mathematics Research Center CIMA UAdeC, Mexico.

[2] In the spatial context, heterogeneity can be caused by the relationship between the independent and dependent variables that vary throughout the space due to local conditions (Anselin, 1988). Other sources of heterogeneity in linear models can mainly arise from omitted variables, causing the error terms to be correlated with the included predictors, unaccounted interaction effects between variables or model misspecification. Our work focuses only on the spatial aspects of nonconstant functional relationships. This means that a single global linear regression model may not adequately capture the variable relationships between different regions, as the coefficients of the regression model may differ between locations.

https://doi.org/10.1016/j.econmod.2025.107139
Received 1 February 2024; Received in revised form 8 May 2025; Accepted 10 May 2025
Available online 27 May 2025

The method is applied to road and territory planning services in Italian municipalities, using spatial data developed by the Solutions for the Economic System S.p.a. (SOSE, https://www.sose.it/en) and the Institute for Local Finance and Economics (IFEL, https://www.fondazioneifel.it). We consider urban traffic services to be one of the fundamental municipal functions intended to meet citizens' primary needs, given the pressing issue of road congestion in metropolitan areas of many European cities (Garcia-López et al., 2022). This function is also a key area for municipalities from a financial perspective. It suits our spatial regime analysis because roads connect different territories and span medium to large areas.

Rather than relying solely on intrinsic characteristics, these areas should be defined through a cost function to ensure cost efficiency and territorial optimality (Castells and Solé-Ollé, 2005; Jerch et al., 2017). Consequently, such areas must be empirically identified with the quantile estimation. Moreover, the spatial quantile approach allows more gradual and consistent paths towards recovery from inefficiency for local public administrations, i.e., "*going beyond the models for the conditional mean*" (Koenker and Hallock, 2001).

The empirical results on urban traffic services highlight substantial territorial disparities and underscore the need for nuanced policy recommendations to address the redistribution of resources between municipalities. The findings stress the importance of recognising and responding to the different economic characteristics of various clusters to design effective and targeted policy interventions.

From a policy viewpoint, our results offer a new toolkit to policymakers when allocating public resources across territories within a country, which generally proves to be a technically demanding and politically sensitive task, as well as essential for both efficiency and equity objectives in advanced economies (Porcelli and Vidoli, 2020) as well as in developing countries (Gupta and Verhoeven, 2001; Apeti et al., 2024). Rather than adopting the simple, unique standard need approach (Boadway, 2004; Lin, 2010), we can fully account for the territorial dimensions that include not only geographic and environmental characteristics but also latent information and variables related to heterogeneous space, which are relevant and usually neglected in previous analyses.

In economic terms, our methodology allows for more reasonable and appropriate comparisons between efficient and inefficient municipalities that belong to the same homogeneous territorial area. This makes it possible to overcome the simple *one against all* approach, where each city is compared to each other, and the outgoing ranking could give a misleading picture in terms of municipal performance, management, and services provided to citizens, as well as financial misallocation of public resources.

The remainder of the paper is organised as follows. Section 2 describes the spatially constrained cluster-wise quantile regression approach that underlies the empirical analyses. Section 3 describes the properties and robustness of the algorithm in the presence of spatial heterogeneity by using some simulations. Section 4 applies the methodology to Italian municipalities based on actual data on road and territory planning services. Finally, Section 5 concludes with some policy recommendations.

2. Regionalisation and spatial heterogeneity: The methodological proposal

The central intuition behind spatial clustering analyses is that the characteristics of units in space considered collectively can capture latent spatial factors. Starting from Openshaw (1973) seminal proposal, many authors (Automatic Zoning Procedure (AZP), Openshaw, 1977 and extended by Openshaw and Rao (1995); max-p, Duque et al., 2012; Skater, Assuncao et al., 2006) have proposed different approaches to define homogeneous areas in terms of spatial units under analysis as a way to address some of the consequences of the modifiable areal unit problem (MAUP). However, the geographical analysis of data in space faces many methodological problems.

One of these issues is that neighbouring units may belong to different spatial clusters. Thus, "fragmented clusters" are not intrinsically invalid, especially if we are interested in exploring the general structure and geography of the multivariate data. Still, in some cases, we are interested in detecting communities or neighbourhoods (as is sometimes needed when drawing electoral or census boundaries), which are almost always different self-connected areas. From an economic standpoint, this involves identifying uniform regions within the territory rather than merely homogeneous points, since specific policies are frequently implemented across entire regions rather than on a municipality-by-municipality basis.

To ensure that clusters are not spatially fragmented, supervised rationalisation methods (SRM) have been proposed (see *e.g.* Duque et al., 2007). SRMs are clustering techniques that also impose a spatial constraint on clusters. In other words, the result of a rationalisation algorithm contains clusters with geographically consistent areas and consistent and internally connected data profiles.

The SRM models in the existing literature aggregate close and similar units for some dimensions $\boldsymbol{X}$, but are not informative on their relationship and, in particular, on the impact of these $\boldsymbol{X}$ on a response variable Y. For this reason, several methods have been recently proposed to estimate spatial regimes,[3] where the term '*regime*' is linked to a regressive relationship underlying the spatial process. Therefore, identifying different spatial regimes is equivalent to estimating different functional regimes of production, while the term '*cluster*' does not presuppose any functional relationship between the variables considered.

Estimating different functional regimes of production implies a discrete non-stationarity of the regressive model compared to the standard stationary one, in which the parameters are fixed or valid throughout the territory. In this vein, the SkaterF algorithm[4] proposed by Vidoli et al. (2022) adopts a non-stationary discrete estimation perspective for areas of contiguous units. More specifically, the SkaterF algorithm can be described as "*a k-means clustering procedure in which the units belong to a proximity [spatial] graph: each observation thereby belongs to the cluster with the nearest mean (measured in terms of distance), to partition n neighbouring observations into k clusters*" (Vidoli et al., 2022). By doing so, the procedure ensures that the estimated clusters reflect geographic proximity and economic characteristics, making policies implemented on homogeneous partitions of municipalities, for example, more consistent, accurate and microfounded.

Then, different marginal effects on the dependent variable for different internally connected areas can be estimated for the expected or average value of a response variable and the estimation of a minimum cost or maximum production function. The proposed methodology[5] therefore extends the SkaterF spatial estimation algorithm developed by Vidoli et al. (2022) using, instead of an OLS specification, quantile regression (QR) techniques (see Koenker and Bassett, 1978; Koenker and Hallock, 2001).

Our proposal can be interpreted as a "truly regional" model where the term regional should be understood as homogeneous functional areas, not in terms shaped by socioeconomic administrative norms, i.e., minimum cost (or maximum production), but within "truly regional" areas. It can even be interpreted as a discretisation of the space

[3] (Classification Analysis Regression Tree (CART), Postiglione et al., 2010; Simulated Annealing (SA), Postiglione et al., 2013, Adaptive Geographically Regression (AGWR) Billé et al., 2017, 2018).

[4] For a more detailed description of the algorithm and its properties, please see Vidoli et al. (2022) and Assuncao et al. (2006).

[5] The Quantile SkaterF function is available on CRAN: https://cran.r-project.org/web/packages/SpatialRegimes/index.html with relative help; codes for subsequent simulations and applications are available from the authors upon request.

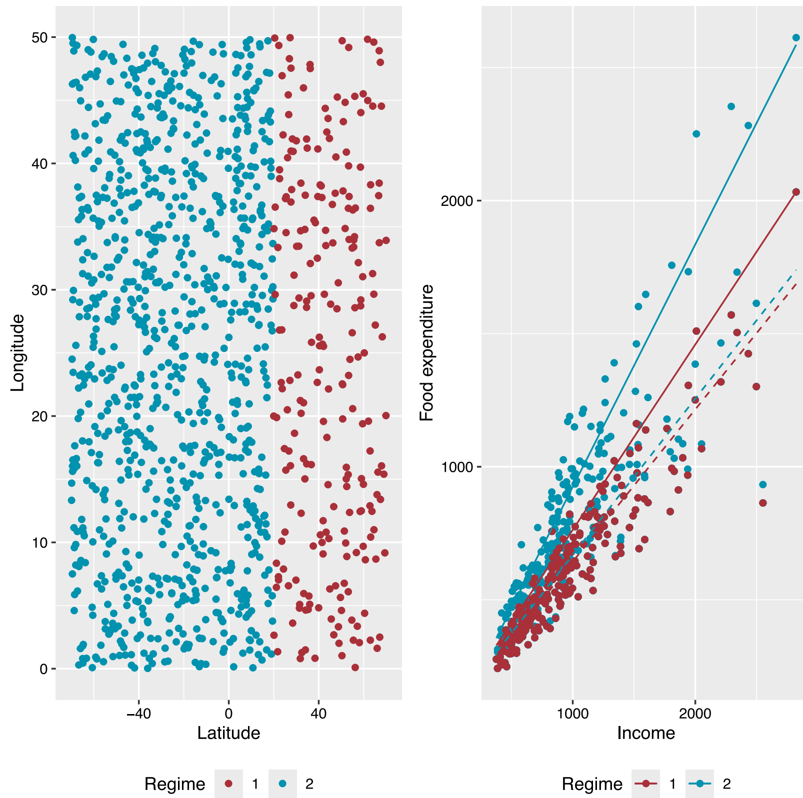

Fig. 1. Simulated data — spatial regimes and quantile 0.50 and 0.93.

of the socioeconomic region that allows units within such space to be evaluated as homogeneous in comparison with a minimum cost or a maximum production.

2.1. Spatial quantile regimes

The critical aspect of the methodology lies in the measurement of the distance between units that, unlike standard clustering methods, are measured in terms of error from a regressive specification (OLS in the original approach, QR in this proposal) to identify clusters of adjacent units,[6] which are the most similar (homogeneous) to each other in terms of distance from the mean estimate (*within*) and, at the same time, the most dissimilar from each other (*between them*). In the proposed approach, quantile regression estimation and homogeneous spatial division are carried out in a single stage since the functional form defines spatial heterogeneity and vice versa. Classical methods such as local estimation approaches (as *e.g.,* Geographically Weighted Regression (GWR) or Muller et al., 2013) only allow verifying the non-stationarity of a functional form without identifying homogeneous spatial regimes.

Therefore, the functional specification can be defined generally and extended to approaches that do not allow making many assumptions about the distribution of the parameters (*i.e.,* a non-parametric approach). Moreover, it is flexible enough to describe economic agents' behaviours in average terms and the most efficient ones, such as the QR. Thus, this is a substantial improvement due to the proposed approach.

It is known that QR is a regressive technique that aims to estimate the conditional τ_{th} quantile of a response variable y given covariates $\mathbf{x} = (x_1, \dots, x_q)$, and – assuming a linear relationship between y and $\mathbf{x}$ – it can be formulated as follows:

$$Q_y(\tau|\mathbf{x}) = x^T \boldsymbol{\beta}(\tau) \tag{1}$$

where $\tau \in (0, 1)$ is the quantile and the coefficient vectors $\boldsymbol{\beta}(\tau)$ are non-smooth functions and play a key role in QR models.[7] Estimating the effects of explanatory variables on specific quantiles of the explained variable allows for obtaining more informative evidence about the differential impact of those variables on the entire distribution of the conditional distribution. It can be a powerful tool to analyse heterogeneous policy impacts on the tails of distributions (*e.g.,* Hardle et al., 2016).

Given a functional form $f(\cdot)$ defining the dependent variable y in terms of covariates $\mathbf{x}$, it is necessary to identify a measure describing the distance of the single incoming unit (into a generic sub-graph) from the relation estimated on that sub-graph in a generic step of the algorithm. In other words, the incoming unit will be assigned to the generic proximity sub-graph based on the minimum distance calculated in terms of estimation error.

What measure can be taken in quantile models to explain how much of the variability is described by the predictor variables and, consequently, measure the impact of including a generic unit within the sub-graph (such as the residual sum of squares in the OLS SkaterF algorithm)? The classical measures cannot be translated into QR. Still, this

[6] The spatial contiguity constraint is included in the analysis through a proximity graph identified using the Minimum Spanning Tree (Pettie and Ramachandran, 2000) algorithm. In particular, we use one of the MST properties (which extends to any other Spanning Tree algorithms): when k links are removed, $k + 1$ regimes are generated. See Vidoli et al. (2022) for further details.

[7] The QR proved to be robust against outliers of the dependent variable and more efficient than traditional OLS regressions. This occurs mainly when skewed distributions characterise the error term; the error is not normally distributed (Furno and Vistocco, 2018).

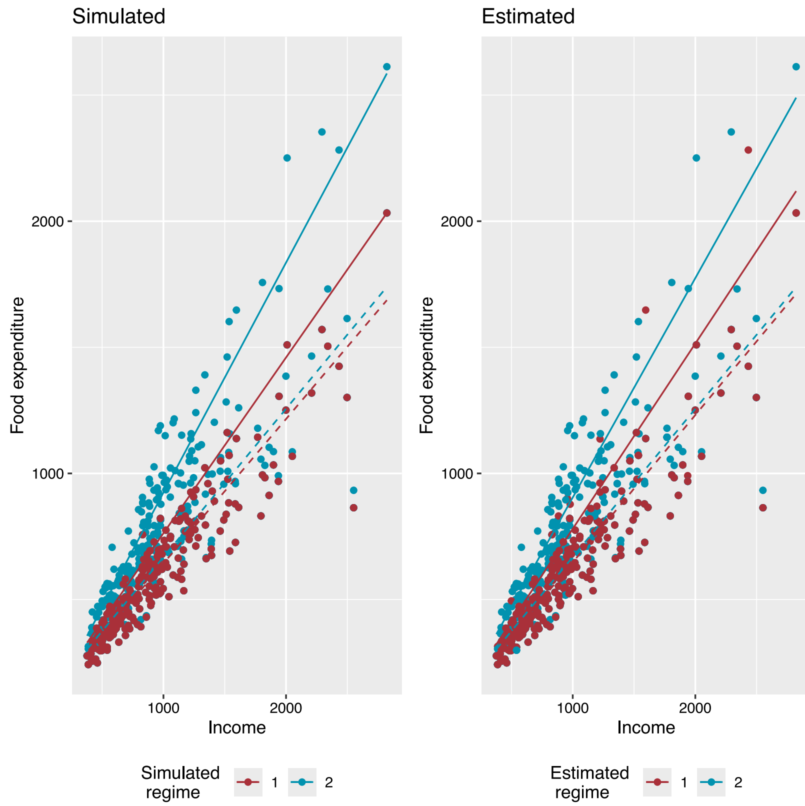

Fig. 2. Estimated and simulated data on quantile 0.50 (dashed lines) and 0.93 (solid lines) by regime.

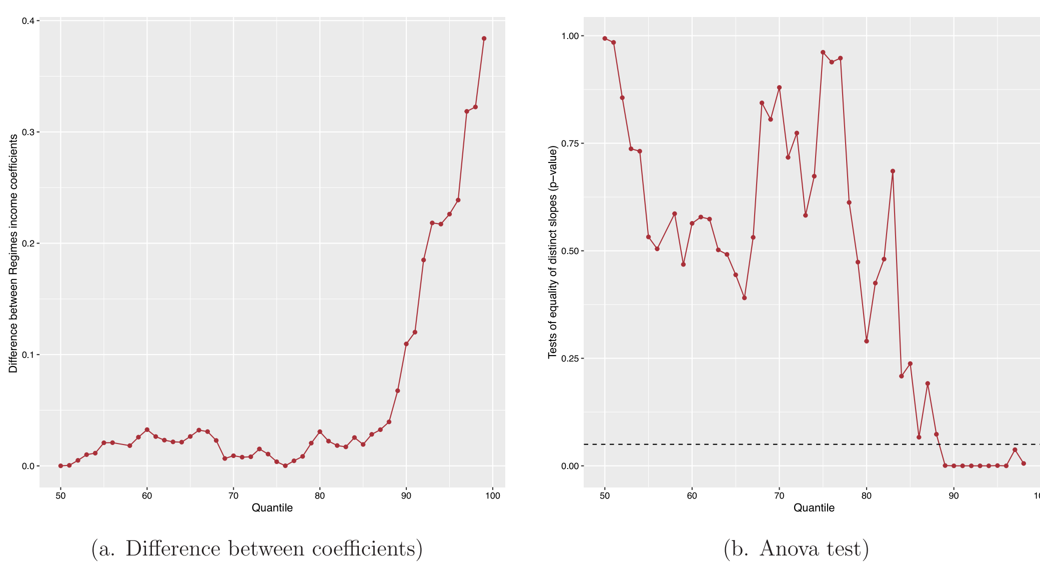

Fig. 3. Difference between spatial regimes income coefficients varying quantile ($k = 2$), quantile τ VS. quantile $\tau - 1$.

shortcoming can be overcome by the result of Koenker and Machado (1999) that proposes a local goodness-of-fit measure (named R^1) in a particular (τ) quantile. Let us define:

$$V(\tau) = \min_b \sum \rho_\tau(y_i - \mathbf{x}_i b) = \min_b \sum \rho_\tau(\epsilon_i) \quad (2)$$

where ρ_τ is a function of the residuals ϵ_i defined as $\epsilon_i(\tau - I(\epsilon_i < 0))$ following Koenker and Bassett (1978).

The idea is to compute two measures: $\tilde{V}(\tau)$ for a model with a single intercept and $\hat{V}(\tau)$ for an unrestricted model. Using these quantities, the goodness-of-fit criterion is defined as:

$$R^1(\tau) = 1 - \hat{V}(\tau)/\tilde{V}(\tau) \quad (3)$$

where $R^1(\tau)$ can be broadly intended as a fitting measure. It can measure the change in the goodness of fit to the quantile model at the level τ for each unit that enters into the spatial sub-graph at each algorithm step.

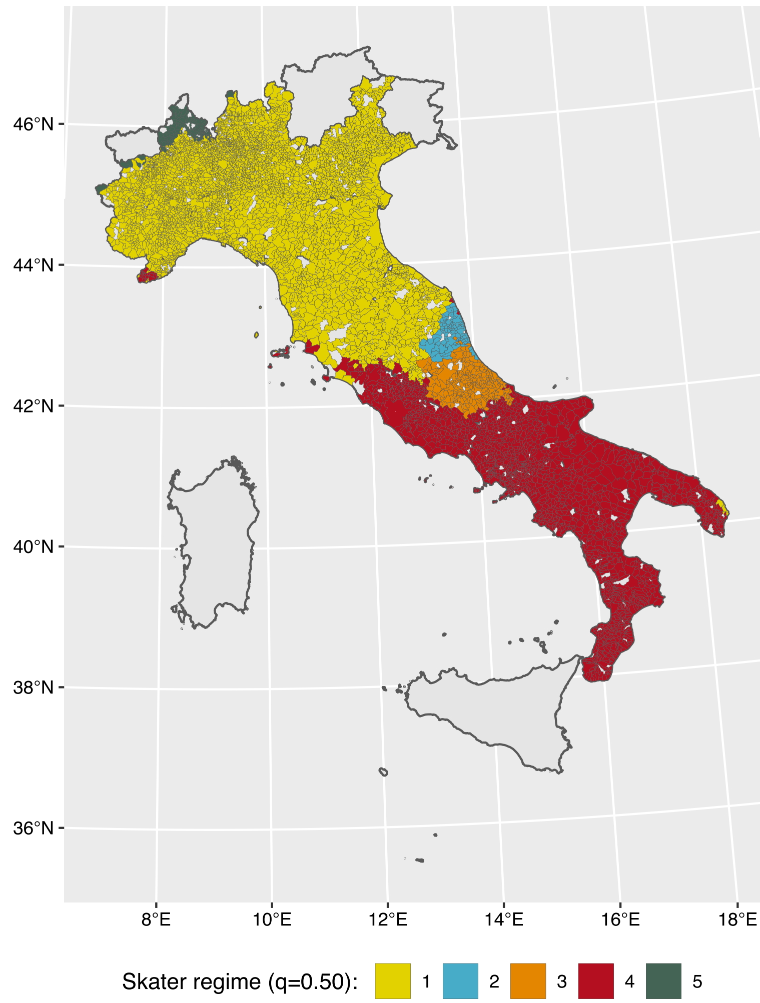

Fig. 4. Estimated spatial regimes ($\tau = 0.50$).

3. Simulations and economic insights

3.1. The simulation setting

This section is devoted to examining the econometric properties of the method and highlighting its suitability in estimating different economic backgrounds that are often heterogeneous to make coherent and feasible policy choices. The Engel curve[8] is used for simplicity, and without loss of generality, in the presence of two spatial regimes for the simulations.[9]

The Data Generating Process aims to obtain two groups of units close to each other in space with a very similar average ratio between expenditure and income, which differs as the reference quantile increases.[10]Thus, there is no difference between territories, on average, while this difference becomes more evident when the relationships, which insist on more extreme quantiles, are considered.

In Appendix A, in Fig. A.7, the simulated data is plotted, showing that the distribution of the simulated data (without making the two territorial regimes evident) highlights substantial stability of the elasticity of the variable income over the dependent as the reference quantile changes. There is no information on whether the units belong to an economic territory. Thus, it would have been easy to conclude a substantial homogeneity of the relation between expenditures and income when the reference quantile also varies for all units analysed.

Without highlighting the territory, it is impossible to understand the functional heterogeneity of the two simulated groups, nor do they behave differently in quantile terms. From a policy viewpoint, ignoring local governments' territorial context and functional heterogeneity can lead to inefficient resource allocation, increased inequality, reduced policy effectiveness, and, ultimately, slower economic growth.

Fig. 1 makes it clear (by construction, obviously) how the explanatory variables of the units[11] belonging to the two different territories

[8] It describes how household spending on a particular good or service varies with household income. This economic relationship has been used extensively in the literature to highlight the effects of heterogeneity in quantile estimation (Houthakker, 2016; Chernozhukov et al., 2015; Muller, 2018).

[9] As stated before, the only source of spatial heterogeneity introduced here is the spatially non-constant functional relationship and not other aspects such as omitted or latent factors, such as different consumption propensities of specific subject groups.

[10] Specific details regarding the DGP are available from the authors upon request.

[11] The proposed algorithm, estimating quantile-based relationships over subsets of (spatially close) units, requires a minimum size of analysis unit that depends essentially on: *(i)* the number of covariates (the more covariates, the more units per regime are needed); *(ii)* the number of spatial regimes estimated (the more one divides the territory, the more units are needed); *(iii)* the precision one wants to estimate the expected value of the quantile of Y (the more precision one wants, the more units I must have in the analysis). To control for the number of units in each regime, the minimum number of units that must be in each regime is a parameter available in the algorithm (and thus in the corresponding R function: `crit` parameter in `SkaterF` function).

(234 red points for regime 1 and 936 blue points for regime 2) have a different impact on the entire distribution of the dependent variable. In particular, data for the two spatial regimes (Fig. 1) have been simulated to have no difference on median ($\tau = 0.50$, dotted lines) to the relation Y conditional on X, but to have a substantial difference on the frontier[12] or, otherwise, as the reference quantile increases.

3.2. Estimations

After generating the simulated data, the first step in analysing the estimation properties of the proposed method (see Section 2) is the identification of the neighbourhood through the estimation of a neighbourhood graph based on a distance matrix.[13] From a neighbourhood matrix, the minimum proximity graph among units has been identified (see Fig. A.8 in Appendix A) using the Minimum Spanning Tree (MST, Pettie and Ramachandran, 2000) algorithm that allows identifying closed areas of contiguous units that are homogeneous in functional terms.

The contiguity constraint is a crucial feature of the proposed method, distinguishing it from existing spatial regime construction methods. This constraint enables the formation of continuous, closed areas rather than scattered points across the territory, allowing the procedure to identify "closed and defined" regions. From a policy perspective, this is essential as it delineates and clearly defines the areas where a specific public program or intervention should be implemented.

Once spatial constraints have been identified, it is possible to apply the SkaterF quantile method to identify in a single stage and simultaneously both the relationship between expenditure and income on a generic quantile and the membership of the different groups that best explain the spatial heterogeneity between units. Obviously – and this aspect is a distinctive feature of the proposed algorithm –, whether an individual unit belongs to a specific regime depends on the functional specification and the quantile chosen. In Appendix A, Fig. A.9 shows that a very good algorithm fit is performed on the 2-regime model data at the 0.93 quantile, showing only a few different attributions in some neighbouring units.

The functional estimates of both the median quantile and the 0.93 quantile also appear very similar between the simulated and estimated data (Fig. 2), demonstrating the ability of the proposed algorithm to partition the space into functional regimes correctly.

Finally, Appendix A presents measures of the algorithm's fit to the simulated data, while Appendix C provides a robustness analysis of the estimates as the neighbourhood matrix varies. Two key aspects remain to be considered: *(i)* how to choose the correct number of spatial regimes (we report this discussion in Appendix B) and *(ii)* how to identify the appropriate quantile of reference (in this simulation chosen equal to 0.93).

3.3. Choosing the "right" quantile

This critical choice, typical of the quantile regression framework, can be approached from multiple perspectives: choosing the "right" quantile may depend on the problem under analysis or can be approached from a regressive coefficient variation point of view. It is possible to test the absolute differences of the estimated coefficients (in our case, the income) between spatial regimes and check if there are specific patterns in the curve as the quantile τ increases.

Fig. 3a clearly shows how the absolute differences between the coefficients for the two spatial regimes remain insignificant and begin to differentiate from the quantile $\tau = 0.93$. The qualitative evaluation, reported in Fig. 3a, can also be tested more precisely using a variant of the Wald test described in Koenker and Bassett (1982) where H_0 is the null hypothesis that the slope coefficients of the same models estimated at different quantiles are identical. In our simulation setting, it can be seen that the differences between the quantile (τ) and the previous quantile ($\tau - 1$ varying τ) became significant (Fig. 3a) starting from quantile 0.89 and this difference remains significant (Fig. 3b) for quantile close to 0.90.

In summary, as shown in Fig. 3, the proposed methodology can be helpful to jointly test whether unitary behaviours, for example, administratively delimited territories such as public municipalities – understood in a functional sense – are (i) heterogeneous throughout the territory and (ii) among themselves, regardless of whether they are near each other or far from each other, and also whether such administrative delimitations are correct in terms of homogeneity considering the heterogeneities.

Disregarding spatial quantile approaches, such as the one we have introduced, would have concealed two significant interacting effects: (i) the heterogeneity between the two territories and (ii) the differing behaviours among groups — in this example, those with medium and high expenditure levels. By applying spatial quantile methods, revealing and analysing these variations becomes possible, offering a more nuanced understanding of how different regions and expenditure groups behave. This insight is critical for developing targeted and effective policies for regional diversity and economic segmentation within populations.

4. An application to the Italian municipalities

4.1. The institutional and legislative framework

In recent decades, the structure of local public finances in Italy has been deeply revised to carry out the reform of decentralisation, which started in 2001. After about twenty years, the reform process cannot be considered complete (Court of Auditors, 2021). How allocation and equalisation schemes of public resources across territories should be designed remains a crucial issue, especially after economic crises that undermine the spending capacity of some municipalities and their provision of public services in terms of quality and efficiency (Lago-Peñas et al., 2020).

According to the current legislative framework (since Law 42/2009 and the following implementation decrees), there are six fundamental public functions that Italian municipalities must fulfil (*i.e.,* general affairs, local police, education, environment, urban traffic, social services). The allocation of resources to local governments is such that it must fully cover the costs to manage those functions (IFEL, 2017). Hence, the amount of costs recognised by each municipality should be determined based on standardised spending criteria, reflecting the effective expenditure needs of each territory to overcome potential distortions and inefficiencies related to the discretionary allocation of resources, including the outdated historical spending principle (SOSE, 2020).[14]

Therefore, the question arises: how much do municipalities spend compared to the *standard expenditure needs* or *a minimum expenditure level*? The standard expenditure needs are a policy tool that serves as an efficiency reference to assess the level of expenditure of municipalities given their heterogeneity and to overcome the distortions related to

[12] For this example, without loss of generality, we have chosen to display the 0.93 quantile (solid lines); this choice will be better substantiated in Section 3.3.

[13] As with any spatial analysis, the selection of the distance matrix and the associated metric is inherently subjective and should be tailored to the specific empirical case being examined: in this case, without loss of generality, the most straightforward graph representation of neighbours – a Gabriel graph, which is a subgraph of the Delaunay triangulation of the points – has been selected.

[14] Operationally, the goal of standard expenditure needs is to identify spending components that are directly affected by specific local needs or production costs and, therefore, are considered exogenous to the policymaker action. However, such expenditure items could be recognised for each local unit, allowing for the corresponding differences in financing between the municipalities.

Table 1
Baseline quantile cost specifications, columns 1–4 $\tau = 0.50$, columns 5–6 $\tau = 0.15$.

	Dependent variable: *Historical expenditure — Euro per inhabitant*					
	Land (1)	+Price (2)	+Output (3)	Complete (4)	Complete (5)	Complete significant (6)
Municipal roads (km)	1.302*** (0.177)	1.228*** (0.215)	0.802*** (0.186)	0.893*** (0.200)	0.415* (0.216)	0.654*** (0.136)
Surface area of municipality (kmq)	1.660*** (0.124)	1.125*** (0.198)	1.046*** (0.130)	1.069*** (0.184)	0.358* (0.217)	
Seismic zone with high probability of strong earthquake (0/1)	1.614*** (0.387)	1.927*** (0.393)	1.323*** (0.369)	1.242*** (0.405)	0.370 (0.365)	
Buildings (N.)	14.959*** (1.045)	7.657*** (1.128)	5.303*** (1.169)	3.627*** (1.048)	1.807 (1.170)	
Average labour costs per employee (Euro)		10.258*** (0.845)	2.325** (1.003)	2.278** (0.929)	3.629*** (1.174)	4.245*** (1.051)
Level of services provided (Composite indicator)			14.429*** (1.795)	13.460*** (1.652)	6.304*** (1.816)	7.952*** (1.548)
Tourist presences (N.)				1.077*** (0.115)	0.636*** (0.114)	0.641*** (0.110)
Constant	37.643*** (1.624)	25.800*** (1.896)	23.128*** (2.057)	25.681*** (1.889)	19.435*** (1.953)	17.859*** (1.599)
Quantile	0.50	0.50	0.50	0.50	0.15	0.15
Observations	6412	6412	6412	6412	6412	6412
Akaike Inf. Crit.	72,270	72,044	71,946	71,752	70,366	70,403

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table 2
Median cost (global model and SkaterF model), $\tau = 0.50$.

	Dependent variable: *Historical expenditure — Euro per inhabitant*	
	$\tau = 0.50$	SkaterF $\tau = 0.50$
Municipal roads	1.761*** (0.186)	
Municipal roads (regime 1)		2.529*** (0.250)
Municipal roads (regime 2)		25.040 (15.381)
Municipal roads (regime 3)		4.020*** (1.136)
Municipal roads (regime 4)		0.988*** (0.256)
Municipal roads (regime 5)		3.866 (3.813)
Average labour costs per employee	2.854*** (1.061)	
Labour costs (regime 1)		2.747 (1.679)
Labour costs (regime 2)		−67.086*** (25.242)
Labour costs (regime 3)		13.530* (7.632)
Labour costs (regime 4)		−1.179 (1.448)
Labour costs (regime 5)		16.431 (13.583)
Level of services provided	18.483*** (1.718)	
Level of services (regime 1)		14.097*** (2.226)
Level of services (regime 2)		261.164** (129.886)
Level of services (regime 3)		1.085 (6.104)
Level of services (regime 4)		22.536*** (3.077)
Level of services (regime 5)		5.474 (20.650)
Tourist presences	1.160*** (0.155)	
Tourist presences (regime 1)		1.189*** (0.269)
Tourist presences (regime 2)		0.153 (3.162)
Tourist presences (regime 3)		4.443 (6.301)
Tourist presences (regime 4)		1.318*** (0.058)
Tourist presences (regime 5)		1.147*** (0.149)
Constant	20.261*** (1.865)	
Constant (regime 1)		27.026*** (2.214)
Constant (regime 2)		−305.055* (171.253)
Constant (regime 3)		40.219*** (6.717)
Constant (regime 4)		19.717*** (3.399)
Constant (regime 5)		14.157* (8.024)
Observations	6370	6370
Akaike Inf. Crit.	71,405.190	70,831.750

the historical expenditure criterion when allocating public resources to lower government levels (Delaney, 2019).[15]

[15] The standard expenditure needs should include variables that are exogenous to the action of the policymaker and account for differences in spending between municipalities (https://www.opencivitas.it/en/expenditure-needs).

Experts, bureaucrats, and officials discussing the technical aspects of new criteria have stimulated a broad debate involving political considerations and economic concerns. Those attempts to revise the spending criteria, although inspired by efficiency, effectiveness, and transparency considerations, prove to be a complex task because the geographical structural differences and heterogeneities are rarely considered, leading to impractical benchmarks and unfeasible targets.

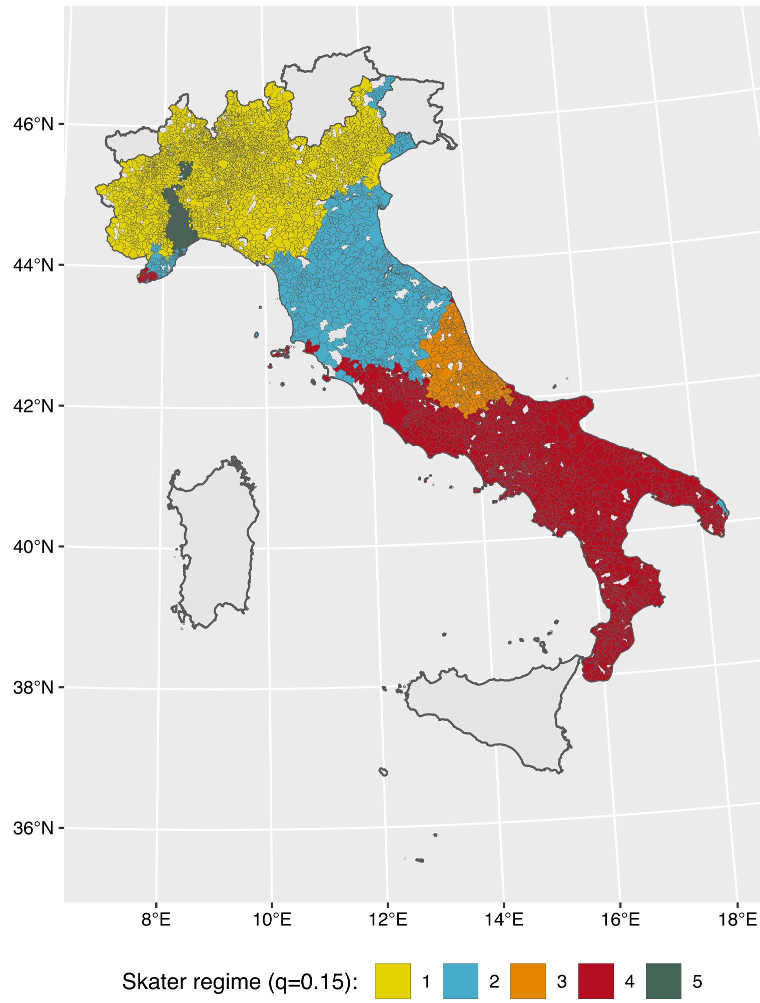

Fig. 5. Estimated spatial regimes ($\tau = 0.15$).

4.2. Roads and territory planning services: motivation and data

Our empirical analysis focuses on roads and territory planning services provided by Italian municipalities as a fundamental function (identified by Legislative Decree 216/2010) and aimed at guaranteeing the accessibility of the road network and urban planning services and land planning, civil protection, and environmental protection for the year 2017.[16] We consider only municipalities belonging to Ordinary Statutory Regions (OSR) in line with the institutional framework and current legislation on determining costs and standard expenditure needs.[17]

Since roads connect different territories, the urban traffic services inherently involve multiple municipalities, which suits our approach. Identifying supra-municipal, contiguous optimal areas fits this service's proper nature and the central government's financial needs. This does not necessarily imply that having a union of municipalities is the best solution. Indeed, recent empirical evidence on the impacts of inter-municipal cooperation on local governments' efficiency is scarce and inconclusive. In the Italian case, the experience of municipal unions on the administrative efficiency of member municipalities for many tasks, including transport services and urban planning, proves to be a failure (Luca and Modrego, 2021; Vidoli et al., 2024).

The dataset, which can be shared through a specific website: https://www.opencivitas.it/en and designed by the SOSE with IFEL members' scientific support, covers more than 6400 municipalities belonging to OSR with information on public spending, cost production, and local variables affecting both local supply and demand sides of public services.

Italian municipalities were grouped into 110 provinces and 20 regions in 2017. About 70% of them have less than 5000 inhabitants, and they spend, as a whole, around 65,000 million euros, which are primarily current expenses. Regarding public spending per capita during 2015–2017, it is approximately 2900 euros in municipalities with fewer than 1000 inhabitants, falling to 1800 euros for municipalities with between 1000 and 3000 inhabitants.[18] The downward trend is around 1200 euros for municipalities with populations between 6000 and 15,000 inhabitants. It reaches up to 3000 euros in larger municipalities, *i.e.,* in cities with more than 1 million residents.[19]

[16] Moreover, as highlighted by previous studies (Jerch et al., 2017), urban traffic represents a suitable standardised output to compare the costs of providing public service by local government.

[17] In fact, the data were initially collected for the sole purpose of calculating financial standard needs for around 6400 municipalities in regions with ordinary statutes and are not available at this level of detail for municipalities in the others.

[18] StatBase: The Italian National Institute of Statistics, https://www.istat.it/en/analysis-and-products/databases/statbase.

[19] A standard feature across territories is the well-known (Tiebout, 1956)'s U-shape function of per capita public expenditure provided by municipalities, mimicking the average cost function of a private firm operating at different

Table 3
Minimum cost (global model and SkaterF model), $\tau = 0.15$.

	Dependent variable: *Historical expenditure — Euro per inhabitant*	
	$\tau = 0.15$ (1)	SkaterF $\tau = 0.15$ (2)
Municipal roads	0.641*** (0.138)	
Municipal roads (regime 1)		0.974*** (0.277)
Municipal roads (regime 2)		0.514 (0.450)
Municipal roads (regime 3)		1.550** (0.629)
Municipal roads (regime 4)		0.611*** (0.223)
Municipal roads (regime 5)		0.932* (0.566)
Average labour costs per employee	4.044*** (1.061)	
Labour costs (regime 1)		2.697 (1.701)
Labour costs (regime 2)		3.777 (3.217)
Labour costs (regime 3)		6.224* (3.273)
Labour costs (regime 4)		1.489 (1.155)
Labour costs (regime 5)		−2.108 (1.635)
Level of services provided	8.193*** (1.550)	
Level of services (regime 1)		7.822*** (2.441)
Level of services (regime 2)		12.745** (5.111)
Level of services (regime 3)		7.646** (3.500)
Level of services (regime 4)		9.084*** (2.898)
Level of services (regime 5)		8.360** (4.179)
Tourist presences	0.642*** (0.109)	
Tourist presences (regime 1)		0.988*** (0.072)
Tourist presences (regime 2)		0.491*** (0.074)
Tourist presences (regime 3)		0.015 (0.637)
Tourist presences (regime 4)		0.397** (0.187)
Tourist presences (regime 5)		2.235*** (0.438)
Constant	17.805*** (1.582)	
Constant (regime 1)		21.926*** (2.482)
Constant (regime 2)		21.624*** (5.809)
Constant (regime 3)		29.214*** (3.016)
Constant (regime 4)		13.957*** (3.359)
Constant (regime 5)		60.014*** (5.579)
Observations	6370	6370
Akaike Inf. Crit.	69,900.090	69,502.070

4.3. Results and discussion

The selection of variables that impact the cost per capita is based on a theoretical model (Blochliger and Charbit, 2008), where the demand for public services interacts with their supply.[20] Still, these methods do not consider the relationship between supply and demand factors or spatial heterogeneity.

In this framework, the efficient cost of each service depends on three key dimensions: *(i)* the quantity of the service provided; *(ii)* the prices of the inputs used in the production process (mainly labour costs); and *(iii)* the contextual covariates of supply and demand. Formally, the functional cost model $f : \mathbb{R}^3 \rightarrow \mathbb{R}$ can be expressed in terms of a unitary cost function y, as $y = f(o, w, x)$, where o is the exogenous outputs or workloads, w is the price vector of labour and capital inputs, and x are the demand factors or the supply contextual variables that represent the morphological and socioeconomic constraints that affect unit production costs.

Table 1 reports the estimated baseline model for both the median per capita expenditure for the urban traffic function ($\tau = 0.50$, columns 1–4) and the 0.15 quantile (columns 5 and 6). The choice of the reference quantile is similar to the criteria shown in Fig. 3, with some differences: in this case, a minimum quantile was searched to verify the stability of the coefficients as the quantile decreases; the average of the distances between the coefficients was chosen as the measure in the presence of several coefficients and not only one as in the simulated case; finally, the ANOVA test (which in the simulated case compared only two groups) is not shown because there are five regimes. Finally, Fig. D.13 uses $\tau = 0.15$ as the reference quantile, as the estimated curves diverge rapidly beyond this quantile.

More specifically, the first column of Table 1 reports the variables of demand (municipal roads, area, buildings) and supply (seismic zone) related to the territory under consideration. In the second column, the model is enriched with the inclusion of the variable labour price; column 3 includes the provided output.[21] In turn, column 4 reports the complete model in the median, including an exogenous demand dimension, tourist presences. The complete model reported in column 4 is helpful because it allows us to evaluate the importance of the covariates as the chosen quantile varies. Finally, column 5 reports the complete model estimates over the 0.15 quantile, while column 6 reports the complete and significant model (even for the 0.15 quantile). The latter cost specification is chosen to apply the SkaterF algorithm to the quantile 0.15 selected as the minimum to obtain robust results across all spatial regimes. This is to avoid some covariates being statistically significant in one regime and not in another.

scale levels. Possible diseconomies of scale occurring at the beginning are gradually absorbed until they reach the minimum cost; beyond that threshold, costs start to increase due, for instance, to congestion problems (Breton, 1965; Ting et al., 2014).

[20] Such approaches represent the standard econometric approach and have been adopted by many scholars (Reschovsky, 2006, 2007; Blochliger and Charbit, 2008; Porcelli and Vidoli, 2020). Other approaches based, for example, on weighted indices (e.g., *Requirements weighted indices expenditure*) can be used for greater simplicity.

[21] This variable is reported in the form of a composite indicator calculated in two stages, with the weights of the first stage determined using the Benefit of the Doubt method (Cherchye et al., 2005) and the average weights of each basic service calculated in the second stage. See https://www.mef.gov.it/export/sites/MEF/ministero/commissioni/ctfs/documenti/Nota_metodologica_FaS_2021_Sose_30set2020.pdf page 50 for more information.

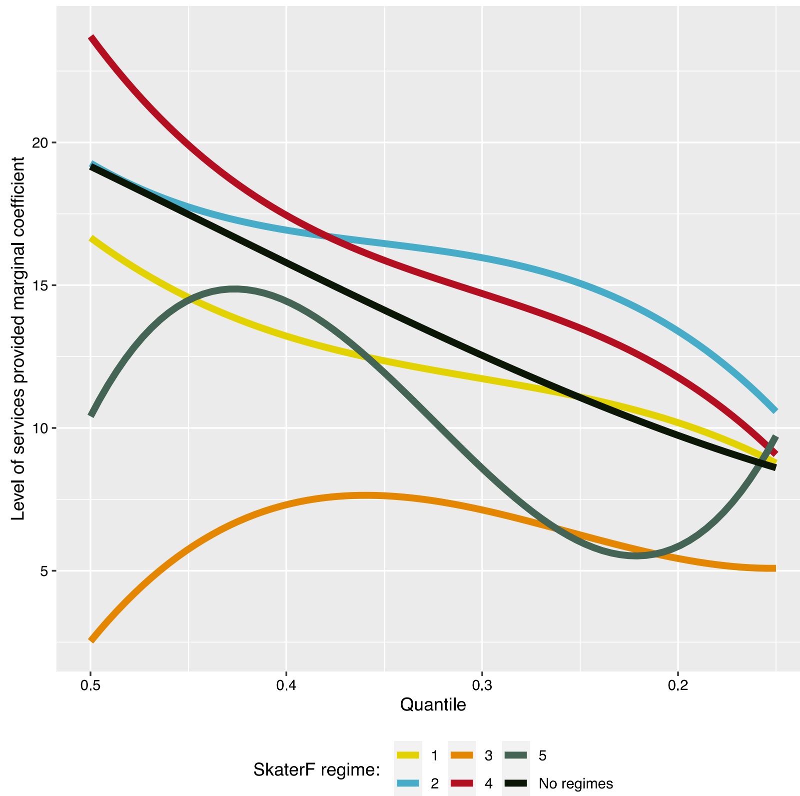

Fig. 6. Trend of the marginal coefficients relative to the output produced varying τ by estimated spatial regime.

Thus, considering the model specified in column 6 (Table 1), it is possible to apply the SkaterF quantile algorithm to characterise homogeneous portions/clusters of territory from a functional point of view. As for the simulated data, calculating the neighbourhood through the Minimum Spanning Tree plot represents the first preliminary step. Fig. D.14 reports the neighbourhood links of the Italian municipalities belonging to the OSR.

By applying our algorithm, it is possible to evaluate the spatial stability of the coefficients for areas and the homogeneous areas obtained (see Table 2 and Fig. 4). Some results emerge:

(i) The marginal coefficients of the individual covariates do not seem globally stable in space;
(ii) Spatial regime 2 appears as an outlier to the global model and the other spatial clusters;
(iii) The differentials between spatial regime 1 (Northern Italy) and 4 (Southern Italy) and the global model in terms of marginal coefficients are significant.

Overall, these findings indicate that the model is not spatially stationary; this suggests that using a single allocation criterion based on global estimates would systematically disadvantage certain areas, leading to long-term structural imbalances. As a result, the assessment of local governments' expenditure needs – central to any intergovernmental fiscal equalisation scheme – would fail to achieve its intended objective, undermining the foundation of sub-national government financing systems (Blochliger and Charbit, 2008).

Moreover, in the long run, an unbalanced allocation of public resources leads to worsening the inter-regional disparities in terms of socioeconomic inequality (Rey and Janikas, 2005) and business opportunities and, as our empirical application demonstrates, generates a negative impact on infrastructure viability, which drives local economic growth.[22]

However, as already pointed out, identifying homogeneous areas in functional terms changes according to the chosen quantile, fundamentally because the subjects of analysis are the efficient behaviours (and no longer the median ones) that yield the maximum homogeneity. This is what happens when we analyse the minimum costs of the Italian municipalities: note that (see Fig. 5) Cluster 2 (labelled in light blue) increases in dimension incorporating part of the North,[23] Cluster 3 (labelled with orange) gives the cross between the Abruzzi and Marche and increases in size. In contrast, Cluster 5 (labelled with grey) remains a small cluster that adds the internal areas between Liguria and Piedmont.

The Table 3, made for estimates of the $\tau = 0.15$ quantiles, shows greater stability than the median data, although there remain clear differences between areas.

In summary, we can argue that there are differences between the marginal coefficients by spatial regime. Such differences reveal a socioeconomic structural heterogeneity among territories that cannot be captured solely through econometric exercises of regional fixed effects. Still, the analysis must consider that all the estimated coefficients are affected (intercept, slope, and error variance). In economic terms, uniformly applying a single minimum cost estimate across the country would mask the underlying disparities between municipalities. This approach would use inappropriate benchmarks, failing to account for regions' varying economic conditions and resource needs, thus obscuring the real differences in their fiscal capacities and expenditure requirements.

[22] As stated by Zouhar et al. (2021), a well-balanced "*public expenditure has been more effective than taxation in reducing inequality*".

[23] It should be noted that, for construction, there is no direct connection between the names of the clusters in the case of $\tau = 0.50$ and $\tau = 0.15$.

Moreover, the marginal coefficients (see Fig. 6) for the output produced remain structurally different between spatial regimes as the quantile varies and compared to the median model.

It can be noted that Cluster 4 (municipalities in the South) and Cluster 2 (Central and Emilia Romagna regions) present, in fact, a structurally higher marginal coefficient than those in the North (cluster 1), which reflects the need to estimate the minimum costs and relative geography in one-stage, as Cluster 3 shows features that are entirely different from the rest of the Italian regions.

This evidence is also robust, varying the minimum quantile compared to the global model (black line) that represents the average trend and converges only near the extreme quantiles of the distribution. Once again, it is evident that the relationship between spending and output is affected by two sources of heterogeneity: the different behaviour between the average municipality and the most efficient in terms of cost, and, intrinsically linked to this, the various spatial effects.

4.4. Limitations, caveats and future research

It is essential to clearly state the limitations and caveats of our approach, as these insights are valuable for future research directions and methodological refinements. Transparency regarding the potential weaknesses of a model not only enhances the credibility of the research, but also serves as a guidepost for future improvements and replication studies. In this context, we identify several relevant issues that merit further discussion.

First, the quantile SkaterF model employed in our analysis is based on a regression framework, in which the conditional quantiles of the response variable are estimated given a set of covariates. As is typical with regression models, any relevant variables omitted from the model specification may be absorbed into the error term, thereby affecting the accuracy and interpretability of the estimated coefficients. This is a general limitation of regression-based techniques: model misspecification or omitted variable bias can influence the validity of the results. In particular, our regime-based structure, although informative and data-driven, may sometimes lead to quantile crossing problems across adjacent regimes or time periods. This issue, discussed by Koenker (2005), arises when the estimated quantile curves are not monotonic with respect to the quantile level, which can undermine the coherence of the results and reduce their practical applicability. Although our neighbourhood structure captures some latent territorial dimensions, it does not necessarily control for all spatially correlated omitted variables or latent factors, which may bias results and weaken inference.

Second, while the proposed quantile regression framework draws directly from the seminal approach by Koenker (2005), it is worth noting that more recent methodological developments have aimed to overcome some of its limitations. For instance, alternative approaches in the literature address the instability of estimates at extreme quantiles and the occurrence of quantile crossing. Specifically, studies such as Chernozhukov (2005) and Li and Wang (2019) have developed techniques that enhance estimation reliability in the tails of the distribution, where data sparsity and heteroskedasticity often challenge standard quantile estimation. In parallel, other researchers have proposed methods that enforce monotonicity constraints across estimated quantile curves, thereby avoiding the quantile crossing issue. For example, the monotonic quantile regression frameworks introduced by Frumento and Bottai (2017) and Frumento and Salvati (2020) and more recently applied in Fusco et al. (2023), offer promising alternatives that preserve the ordered structure of quantiles while maintaining estimation flexibility. These advanced methods could be considered in future research efforts to improve the robustness and coherence of the estimated frontiers, particularly in empirical settings characterised by spatial or structural complexity.

Third, a significant limitation of our approach is the lack of explicit modelling of spatial autocorrelation within regimes. Spatial data often exhibit both spatial heterogeneity, systematic variation in relationships across space, and spatial autocorrelation, the tendency of similar values to cluster geographically. These two properties are conceptually distinct but empirically intertwined, and failure to account for one may obscure the presence of the other. For example, strong spatial autocorrelation can mask true heterogeneity by clustering similar observations, while ignoring heterogeneity may lead to overestimation of spatial dependence. Pioneering works such as Anselin (1988) and subsequent studies (Kostov, 2009; Arbia et al., 2012; Cartone et al., 2021) emphasise that when both are present, it complicates spatial modelling, possibly leading to erroneous conclusions, model misspecification, and inconsistency in estimation procedures, including quantile regression (Kim and Muller, 2004). Incorporating spatial filtering or explicitly modelling spatial effects through spatial econometric models could be promising directions for addressing this issue in future applications.

Advancements in methodology can serve as a foundation for future research and further developments. Despite certain limitations of the proposed approach, its clarity and ease of comprehension make it a preferable standard, ensuring robust results. Moreover, issues related to estimation instability in extreme quantiles (Chernozhukov, 2005; Frumento and Salvati, 2020) are only partially helpful and applicable in particular cases. Similarly, concerns regarding omitted variables or substantial levels of spatial autocorrelation are relevant only in specific contexts.

5. Concluding remarks and policy implications

By applying the proposed methodology to the case of Italian municipalities, we show the efficient conditions for providing public spending under homogeneous regimes, simultaneously considering socio-economic and territorial heterogeneity. The benchmark references emerging from the empirical application can be used to gradually reduce inefficiencies and detect a balanced allocation of public resources that would lead to higher regional convergence, lower inequality, and foster local economic growth.

Our approach is instrumental in assessing the efficiency of local governments where spatial heterogeneity due to omitted and/or latent variables is substantial and where spatial regularities are often not related to precise administrative boundaries. Given the Italian institutional scenario and different heterogeneities across territories, our analysis is suitable for overcoming the described limitations and estimating a partial minimum cost approach. This exercise is interesting not only from an empirical viewpoint but also from a political perspective, identifying equalisation paths for costs and public expenditures of different municipalities.

This issue is not straightforward, as the term "cost efficiency" has been inappropriately used when referring to a simple expenditure function without accounting for actual output data. The function analysed, leveraging Italian data with unprecedented detail, is not merely an expenditure function that directly relates historical expenditure to local supply and demand factors. Instead, it is a cost function that includes output (*i.e.,* the historical service provided by individual municipalities) among its covariates.

Estimating the function based on minimum cost levels accounts for the relationship between expenditure and service levels, ensuring that benchmarks are not set by municipalities that spend less but by those that achieve lower costs while delivering the same level of services. From a policy perspective, this is an essential aspect to be considered for appropriately framing any spending review process in Italy and other countries (Auci et al., 2021; Bucci et al., 2024).

Finally, our approach improves the knowledge of evaluating increasing minimum costs in a quantile framework, considering that different territories will likely have heterogeneous impacts on the production cost of local public services. Future lines of empirical and methodological research could deal with a possible extension of the proposed approach to panel data models, to the inclusion of endogeneity issues within frontier cost models (Karakaplan and Kutlu, 2017) and in the connection between quantile estimation and stochastic frontier estimation (Jradi et al., 2019).

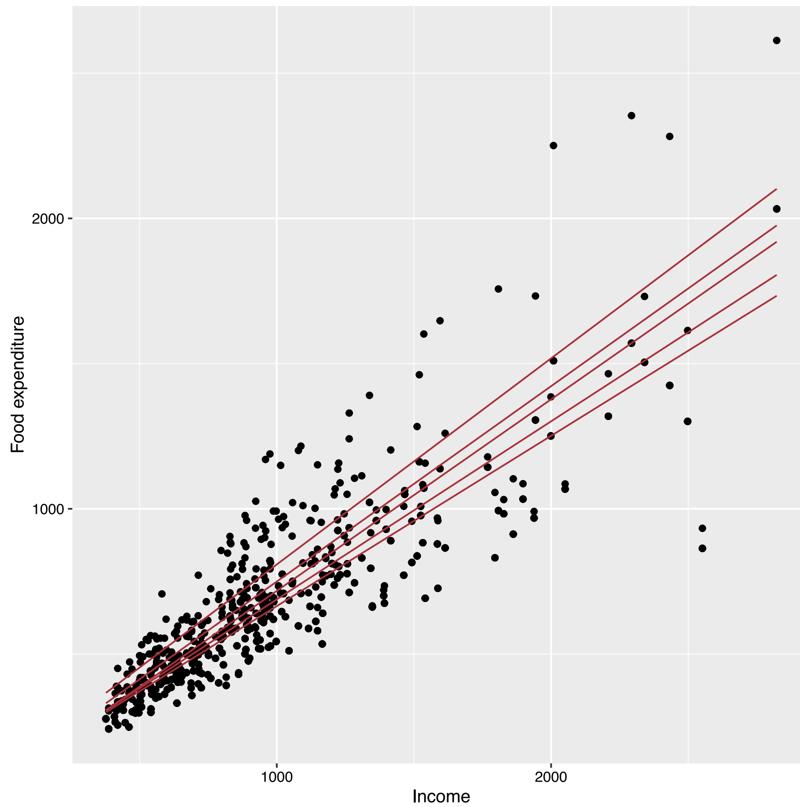

Fig. A.7. Simulated data; quantile 0.50, 0.60, 0.70, 0.80 and 0.90.

Declaration of competing interest

The authors declare that they have not conflicts of interest that relate to the research described in this paper.

Acknowledgements

We are indebted to the Editor, Prof. Sushanta Mallick, the Associate Editor, and two anonymous referees for their helpful suggestions and pertinent comments, which helped us improve the manuscript. Many thanks to Francesco Porcelli, Giovanni Marin, Adrian Risso, and Laura Policardo for their valuable comments on improving our research. The usual disclaimer applies.

Appendix A. Estimates for simulated data

Tables A.4 and A.5 report quantile estimates on the median and the 0.93 quantile, respectively, in both simulated data clusters (columns labelled Clu) as in the spatial regimes identified by the algorithm (identified as Reg). It is easy to note that the estimates on the simulated groups and on the estimated regimes are substantially the same for both group 1 and group 2, while this result changes markedly at the 0.93 quantile. In this case, for group 1 the elasticity is equal to about 0.69, while for group 2 it goes up to 0.91 and is perfectly centred by our algorithm.

Table A.4
Quantile regression ($\tau = 0.50$) by simulated and estimated cluster by regime.

	Dependent variable: *Food expenditure (quantile 0.50)*			
	Clu 1 (1)	Reg 1 (2)	Clu 2 (3)	Reg 2 (4)
Income	0.573*** (0.028)	0.584*** (0.025)	0.588*** (0.014)	0.587*** (0.014)
Constant	70.282*** (18.742)	63.712*** (14.807)	80.820*** (9.794)	81.312*** (9.886)
Observations	234	262	936	908

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table A.5
Quantile regression ($\tau = 0.93$) by simulated and estimated cluster by regime.

	Dependent variable: *Food expenditure (quantile 0.93)*			
	Clu 1 (1)	Reg 1 (2)	Clu 2 (3)	Reg 2 (4)
Income	0.697*** (0.022)	0.735*** (0.070)	0.912*** (0.046)	0.870*** (0.049)
Constant	65.990*** (17.821)	45.506 (35.059)	12.368 (29.134)	34.789 (28.610)
Observations	234	262	936	908

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Appendix B. Hierarchical nature of the algorithm

Identifying the "correct" or the most appropriate number of spatial regimes remains a critical aspect of the proposed procedure, but it takes advantage of an important property of the original SkaterF algorithm (please see, in this respect, Vidoli et al., 2022): the hierarchical nature of the algorithm itself, *i.e.* the property that the $k+1$ estimated spatial regime is contained, from a spatial point of view, completely within one of the k previously estimated regimes.

"*The spatially hierarchical nature of the algorithm ensures that new subdivisions are always included in the corresponding higher level areas*" (Vidoli et al., 2022). The nested property, in fact, is an important aspect in our case, at least for those reasons: first, it is more useful

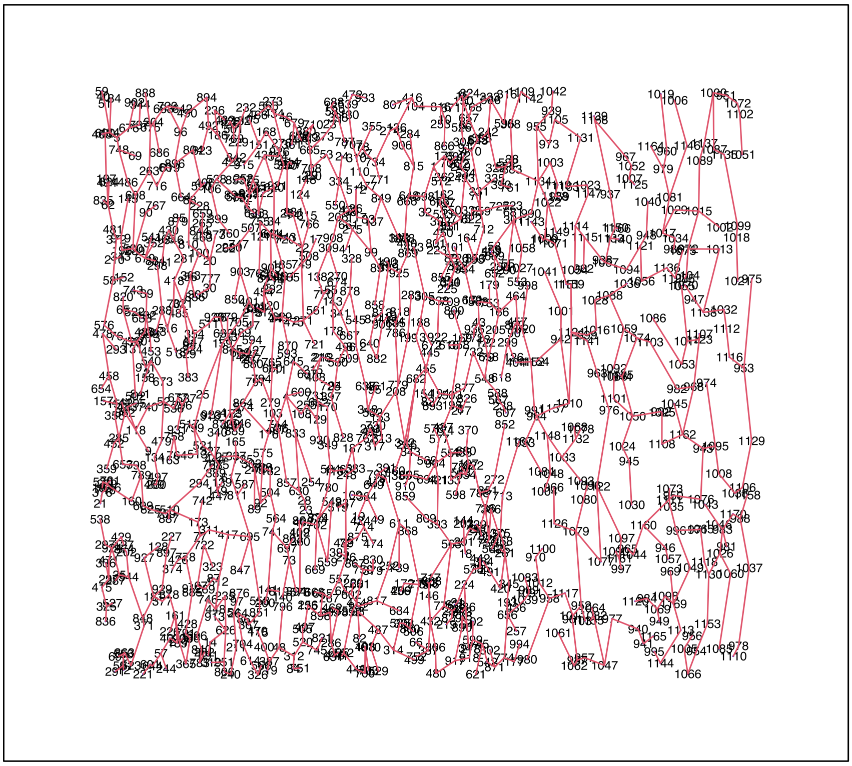

Fig. A.8. Minimum spanning tree, simulated data.

Table A.6
Marginal contributions on income variable varying τ, k = 2.

2 Spatial	τ = 0.50				τ = 0.93			
regimes	Contrast	Std. Err.	z	P>z	Contrast	Std. Err.	z	P>z
2 vs. 1	20.533	8.932	2.30	0.022	89.180	37.949	2.35	0.019

for economic interpretation. Consequently, results can be read in terms of macro-areas and, when increasing the number of regimes, also in terms of sub-areas of such macro-areas already identified. In general, this provides a top-down interpretation criteria. Second, the regression estimates within these higher-level areas are very similar to each other, by construction, in terms of marginal effects. Finally, that property allows for getting robust results: a 'wrong' choice of the number of identified regimes would only affect the accuracy of the estimates in some regimes, while leaving the others unaffected. Fig. B.10 clarifies this property better: on the left, the membership of single points in the two previously estimated spatial regimes is reported, while on the right the estimation is set to 3 clusters (please note that clusters 2 A and 2B have been so named to emphasise the original correspondence to cluster 2, while regime 1 remains exactly identified as in the previous step).

Put differently, when switching to a higher number of regimes, only a greater division of the original clusters is obtained without any change between the clusters, and this occurs with respect to quantile regression estimates as well (Fig. B.11).

It is just by exploiting statistical tests related to quantile regressions that it is possible to obtain a possible criterion to identify the "right" or the optimal number of spatial regimes, that is, by computing the distance between the estimated coefficients in the different spatial-nested models (from a cluster number perspective). However, usual OLS/quantile nested tests are not useful in this spatial framework because the covariates remain only nominally equal across steps and due to the fact that the number of groups changes. Thus, comparing the marginal coefficients with each other through the Wald test remains a valid tool for assessing whether all groups of two spatial regimes have significantly different coefficients. Given these premises and given that the coefficients between regimes 2 A and 2B are not so different, it is verified that it is not necessary to choose more than 2 spatial regimes (see Appendix A, Tables A.6 and A.7).

The complete estimates (on simulated data, on data estimated with $k = 2$ and with $k = 3$) are finally reported in Table B.8. Some findings emerge: *(i)* the estimates reported in column 3 are equal by construction, given the hierarchical property, to column 5 and *(ii)* 908 units in column 4 are split between column 6 (681 units) and column 7 (227) showing that the estimated income coefficient is essentially the same (and different from that of regime 1).

Appendix C. Robustness

Two robustness tests have been implemented: *(i)* varying the type of neighbourhood graph (Fig. C.12) and *(ii)* varying the size of the units under analysis. Concerning the first point, the neighbourhood graphs are reported according to Delaunay triangulation of the points, to the Gabriel graph (a sub-graph of the Delaunay triangulation retaining a different set of neighbours, Matula and Sokal, 1980), to Relative graph neighbours (Toussaint, 1980) and to a Distance-Based Neighbours graph as the $k = 6$ nearest neighbours. The results reported in Table C.9 show very good stability (within 5% of the percentage difference between the estimated coefficients of the actual and estimated regimes for both groups and for the quantiles 0.5 and 0.93 in all cases) with respect to both the simulated data and each other. On the other hand, with regard to robustness in relation to the size of the regimes, Table C.10 reports the percentage difference between the estimated coefficients (quantiles 0.5 and 0.93) of the real and the estimated regime; the percentage differences remain in the range of a maximum of 3%–4%, demonstrating strong robustness to changes in the simulated setting.

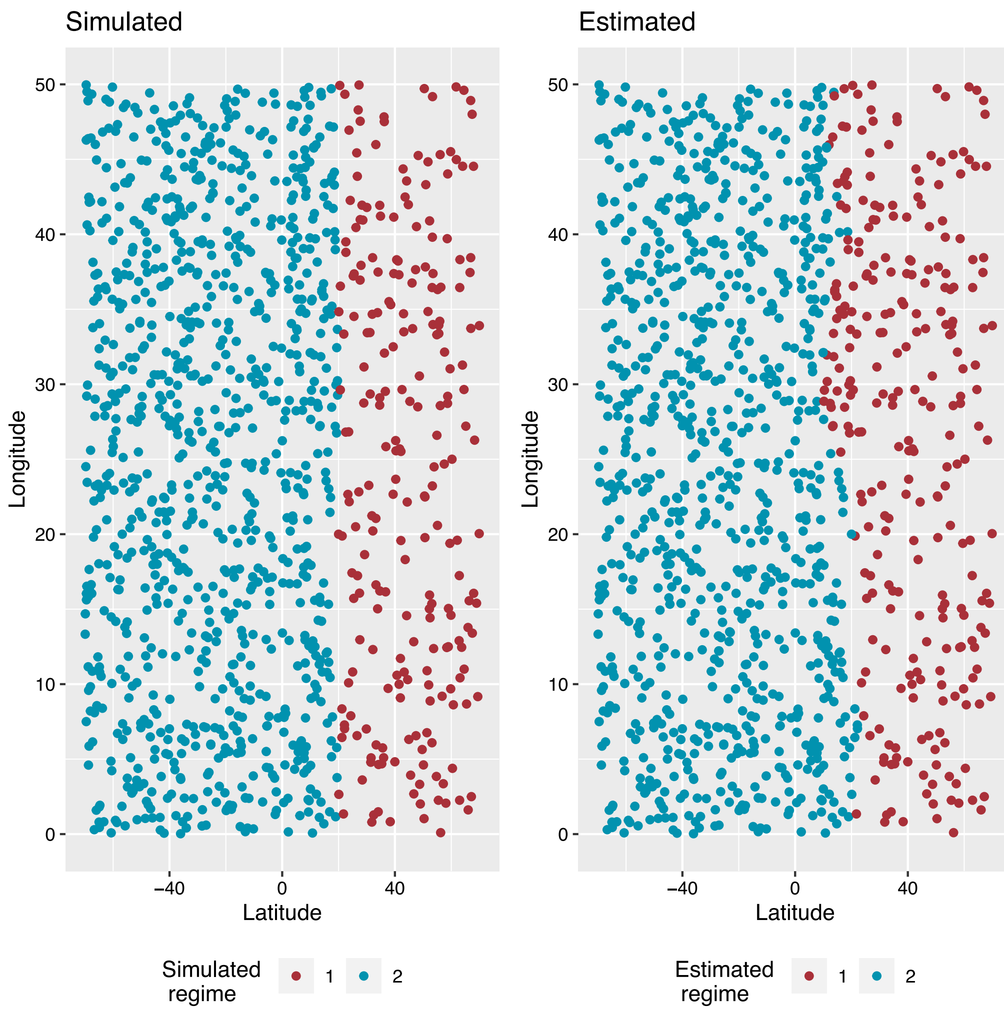

Fig. A.9. Estimated (τ = 0.93) and simulated regimes location by regime.

Table A.7
Marginal contributions on income variable varying τ, k = 3.

3 Spatial	τ = 0.50				τ = 0.93			
regimes	Contrast	Std. Err.	z	P>z	Contrast	Std. Err.	z	P>z
2A vs. 1	20.358	11.320	1.800	0.072	93.535	47.196	1.980	0.047
2B vs. 1	21.165	9.289	2.280	0.023	90.729	38.728	2.340	0.019
2B vs. 2A	0.807	9.626	0.080	0.933	−2.806	40.136	−0.070	0.944

Table B.8
Quantile regression (τ = 0.93) by simulated versus estimated cluster and by regimes.

	Dependent variable: Food expenditure (quantile 93)						
	Simulated		Estimated (2 regimes)		Estimated (3 regimes)		
	Clu 1 (1)	Clu 2 (2)	Reg 1 (3)	Reg 2 (4)	Reg 1 (5)	Reg 2A (6)	Reg 2B (7)
Income	0.697*** (0.022)	0.912*** (0.046)	0.735*** (0.070)	0.870*** (0.049)	0.735*** (0.070)	0.779*** (0.061)	0.930*** (0.088)
Constant	65.990*** (17.821)	12.368 (29.134)	45.506 (35.059)	34.789 (28.610)	45.506 (35.059)	105.836*** (30.763)	−12.440 (60.769)
Observations	234	936	262	908	262	681	227

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Appendix D. Italian municipalities: empirical estimates

See Figs. D.13 and D.14.

Data availability

Data and codes are available at this link: https://data.mendeley.com/datasets/5nrk9f3p24/1.

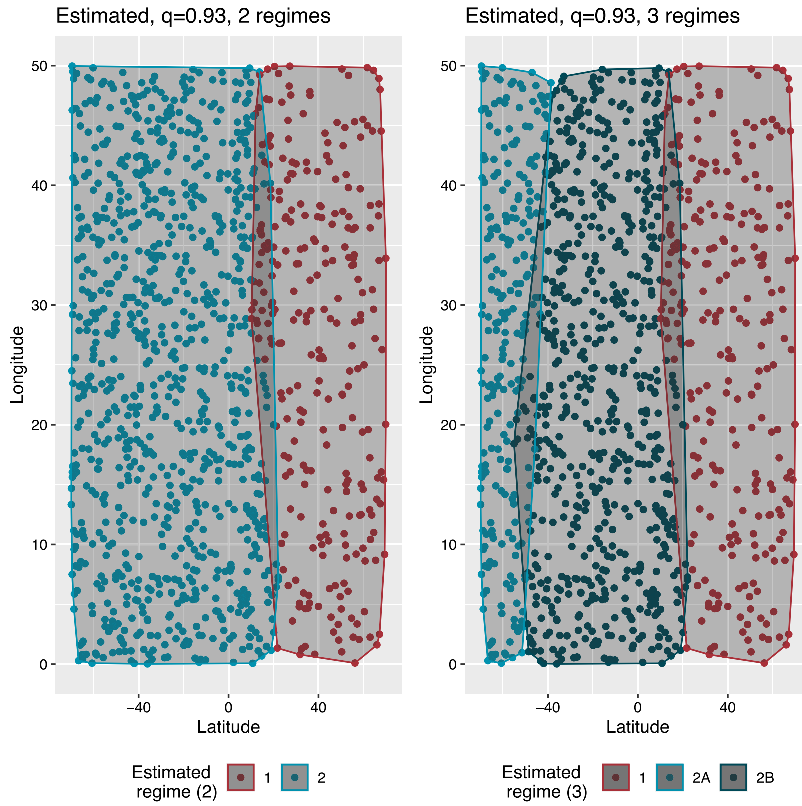

Fig. B.10. Estimated and simulated regimes locations (2 *vs.* 3 estimated regimes).

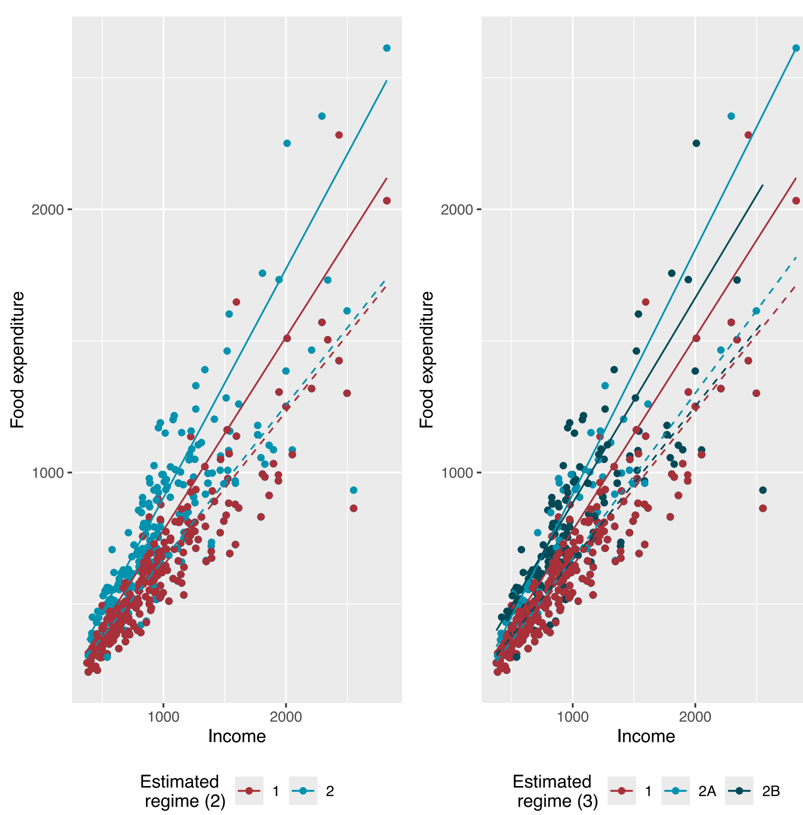

Fig. B.11. Estimated and simulated data on quantile 0.50 (dashed lines) and 0.93 (solid lines) (2 *vs.* 3 estimated regimes).

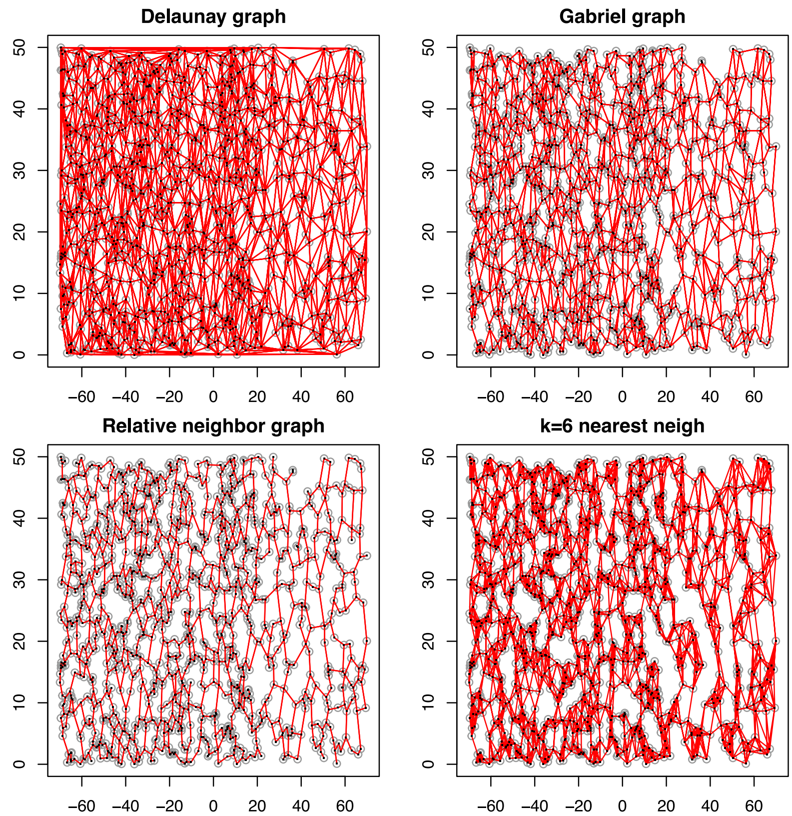

Fig. C.12. Graph-Based neighbours.

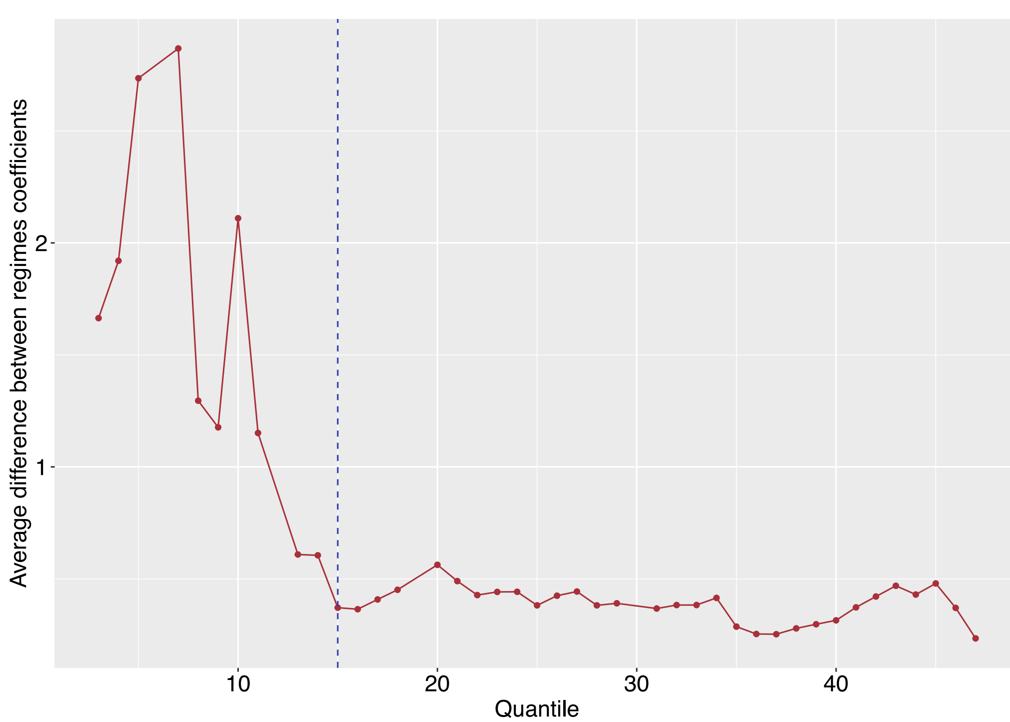

Fig. D.13. Average difference between spatial regimes coefficients varying quantile.

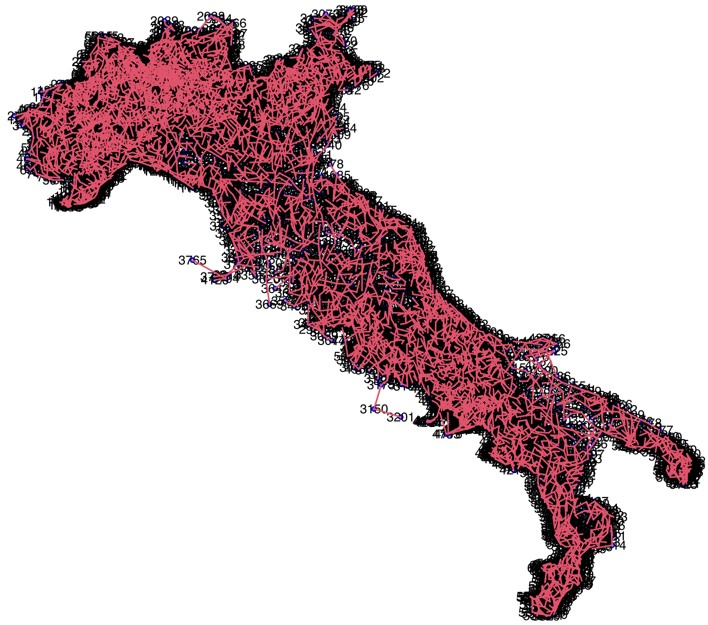

Fig. D.14. Minimum Spanning Tree — Italian municipalities.

Table C.9
Simulations varying the neighbourhood graph.

	Delaunay graph	Gabriel graph	Relative neighbour graph	k = 6 nearest neigh
N. regime #1	234	234	234	234
N. regime #2	936	936	936	936
Perc. Diff. Clu1 VS. Reg1 (τ = 0.50)	1.24	1.92	1.26	1.92
Perc. Diff. Clu2 VS. Reg2 (τ = 0.50)	0.24	0.05	0.24	0.41
Perc. Diff. Clu1 VS. Reg1 (τ = 0.93)	0.48	5.17	0.00	2.38
Perc. Diff. Clu2 VS. Reg2 (τ = 0.93)	0.00	4.82	0.00	2.58

Table C.10
Simulations varying dimension.

	Simulations					
N. regime #1	234	234	234	234	234	234
N. regime #2	936	900	800	700	500	300
Perc. Diff. Clu1 VS. Reg1 (τ = 0.50)	1.24	2.07	2.20	2.20	1.77	2.00
Perc. Diff. Clu2 VS. Reg2 (τ = 0.50)	0.24	0.00	0.89	0.27	1.91	0.62
Perc. Diff. Clu1 VS. Reg1 (τ = 0.93)	0.48	0.22	0.74	1.33	1.73	0.00
Perc. Diff. Clu2 VS. Reg2 (τ = 0.93)	0.00	0.07	0.42	0.06	4.31	0.85

References

Afonso, A., Fernandes, S., 2006. Measuring local government spending efficiency: Evidence for the lisbon region. Reg. Stud. 40 (1), 39–53.

Afonso, A., Jalles, J.T., Venâncio, A., 2024. Fiscal decentralization and public sector efficiency: Do natural disasters matter? Econ. Model. 137, 106763.

Anselin, L., 1988. Spatial Econometrics: Methods and Models, vol. 4, Springer Science & Business Media.

Apeti, A.E., Bambe, B.-W.-W., Lompo, A.A.B., 2024. Determinants of public sector efficiency: a panel database from a stochastic frontier analysis. Oxf. Econ. Pap. 76 (3), 741–758.

Arbia, G., Espa, G., Giuliani, D., Mazzitelli, A., 2012. Clusters of firms in an inhomogeneous space: The high-tech industries in Milan. Econ. Model. 29 (1), 3–11.

Assuncao, R., Neves, M., Camara, G., Da Costa Freitas, C., 2006. Efficient regionalization techniques for socio-economic geographical units using minimum spanning trees. Int. J. Geogr. Inf. Sci. 20 (7), 797–811.

Auci, S., Castellucci, L., Coromaldi, M., 2021. How does public spending affect technical efficiency? Some evidence from 15 European countries. Bull. Econ. Res. 73 (1), 108–130.

Balaguer-Coll, M.T., Prior, D., Tortosa-Ausina, E., 2010. Decentralization and efficiency of local government. Ann. Reg. Sci. 45 (3), 571–601.

Billé, A.G., Benedetti, R., Postiglione, P., 2017. A two-step approach to account for unobserved spatial heterogeneity. Spat. Econ. Anal. 12 (4), 452–471.

Billé, A.G., Salvioni, C., Benedetti, R., 2018. Modelling spatial regimes in farms technologies. J. Prod. Anal. 49 (2), 173–185.

Blochliger, H., Charbit, C., 2008. Fiscal equalisation. OECD J.: Econ. Stud. 1, 1–22.

Boadway, R., 2004. The theory and practice of equalization. CESifo Econ. Stud. 50 (1), 211–254.

Bordignon, M., Cerniglia, F., Revelli, F., 2003. In search of yardstick competition: a spatial analysis of Italian municipality property tax setting. J. Urban Econ. 54 (2), 199–217.

Breton, A., 1965. Scale effects in local and metropolitan government expenditures. Land Econ. 41 (4), 370–372.

Bucci, V., Ferrara, G., Resce, G., 2024. Local government spending efficiency and fiscal decentralization: evidence from Italian municipalities. Appl. Econ. 56 (5), 599–614.

Cartone, A., Postiglione, P., Hewings, G.J., 2021. Does economic convergence hold? A spatial quantile analysis on European regions. Econ. Model. 95, 408–417.

Castells, A., Solé-Ollé, A., 2005. The regional allocation of infrastructure investment: The role of equity, efficiency and political factors. Eur. Econ. Rev. 49 (5), 1165–1205.

Cherchye, L., Lovell, K., Moesen, W., Puyenbroeck, T.V., 2005. One Market, One Number? A Composite Indicator Assessment of Eu Internal Market Dynamics. Technical report, Working Paper Series ces0513, Katholieke Universiteit Leuven, Centrum voor Economische Studien.

Chernozhukov, V., 2005. Extremal quantile regression. Ann. Statist. 33 (2), 806–839.

Chernozhukov, V., Fernandez-Val, I., Hoderlein, S., Holzmann, H., Newey, W., 2015. Nonparametric identification in panels using quantiles. J. Econometrics 188 (2), 378–392.

Choudhury, A., Sahu, S., 2023. Reconciling the mixed evidence in the fiscal decentralization-government size nexus using panel quantile regression. Econ. Model. 125, 106347.

Ciccarelli, C., Elhorst, J., 2018. A dynamic spatial econometric diffusion model with common factors: The rise and spread of cigarette consumption in Italy. Reg. Sci. Urban Econ. 72, 131–142.

Court of Auditors, 2021. Rapporto 2021 sul Coordinamento della Finanza Pubblica. Technical Report, Court of Auditors.

Delaney, J., 2019. Comparing apples to apples: Estimating fiscal need in the United States with a regression-based representative expenditure approach. Atl. Econ. J. 47 (3), 311–322.

Duque, J.C., Anselin, L., Rey, S.J., 2012. The MAX-P-regions problem. J. Reg. Sci. 52 (3), 397–419.

Duque, J.C., Ramos, R., Suriñach, J., 2007. Supervised regionalization methods: A survey. Int. Reg. Sci. Rev. 30 (3), 195–220.

Egan, E.J., Brander, J.A., 2022. A new method for identifying and delineating spatial agglomerations with application to venture-backed startups. J. Econ. Geogr. 23, 485–508.

Frumento, P., Bottai, M., 2017. Parametric modeling of quantile regression coefficient functions with censored and truncated data. Biometrics 73 (4), 1179–1188.
Frumento, P., Salvati, N., 2020. Parametric modelling of M-quantile regression coefficient functions with application to small area estimation. J. R. Stat. Soc. Ser. A Stat. Soc. 183 (1), 229–250.
Furno, M., Vistocco, D., 2018. Quantile Regression: Estimation and Simulation, Volume 2, vol. 216, John Wiley & Sons.
Fusco, E., Benedetti, R., Vidoli, F., 2023. Stochastic frontier estimation through parametric modelling of quantile regression coefficients. Empir. Econ. 64 (2), 869–896.
Gaigné, C., Riou, S., Thisse, J.-F., 2016. How to make the metropolitan area work? Neither big government, nor laissez-faire. J. Public Econ. 134, 100–113.
Garcia-López, M.-À., Pasidis, I., Viladecans-Marsal, E., 2022. Congestion in highways when tolls and railroads matter: evidence from European cities. J. Econ. Geogr. 22 (5), 931–960.
Geys, B., 2006. Looking across borders: A test of spatial policy interdependence using local government efficiency ratings. J. Urban Econ. 60 (3), 443–462.
Goel, R.K., Mazhar, U., Nelson, M.A., Ram, R., 2017. Different forms of decentralization and their impact on government performance: Micro-level evidence from 113 countries. Econ. Model. 62, 171–183.
Gupta, S., Verhoeven, M., 2001. The efficiency of government expenditure: experiences from Africa. J. Policy Model. 23 (4), 433–467.
Hardle, W., Wang, W., Yu, L., 2016. Tenet: Tail-event driven network risk. J. Econometrics 192 (2), 499–513.
Houthakker, H.S., 2016. Engel curve. In: Durlauf, S., Blume, L.E. (Eds.), The New Palgrave Dictionary of Economics. Palgrave Macmillan UK, London, pp. 1–4.
IFEL, 2017. Temi Per l'Analisi Degli Effetti della Perequazione Delle Risorse Comunali. contributo alla Discussione della Commissione Tecnica per I Fabbisogni Standard, IFEL, Roma.
Jerch, R., Kahn, M.E., Li, S., 2017. The efficiency of local government: The role of privatization and public sector unions. J. Public Econ. 154, 95–121.
Jradi, S., Parmeter, C.F., Ruggiero, J., 2019. Quantile estimation of the stochastic frontier model. Econom. Lett. 182, 15–18.
Karakaplan, M., Kutlu, L., 2017. Handling endogeneity in stochastic frontier analysis. Econ. Bull. 37 (2), 889–901.
Kim, T.-H., Muller, C., 2004. Two-stage quantile regression when the first stage is based on quantile regression. Econom. J. 7 (1), 218–231.
Koenker, R., 2005. Quantile Regression. Cambridge Books, Cambridge University Press.
Koenker, R., Bassett, G., 1978. Regression quantiles. Econometrica 46 (1), 33–50.
Koenker, R., Bassett, G., 1982. Robust tests for heteroscedasticity based on regression quantiles. Econometrica 50, 43–61.
Koenker, R., Hallock, K.F., 2001. Quantile regression. J. Econ. Perspect. 15 (4), 143–156.
Koenker, R., Machado, J.A.F., 1999. Goodness of fit and related inference processes for quantile regression. J. Amer. Statist. Assoc. 94 (448), 1296–1310.
Kostov, P., 2009. A spatial quantile regression hedonic model of agricultural land prices. Spat. Econ. Anal. 4 (1), 53–72.
Lago-Peñas, S., Martinez-Vazquez, J., Sacchi, A., 2020. Fiscal stability during the great recession: putting decentralization design to the test. Reg. Stud. 54 (7), 919–930.
Li, D., Wang, H.J., 2019. Extreme quantile estimation for autoregressive models. J. Bus. Econom. Statist. 37 (4), 661–670.
Lin, C.-Y.C., 2010. How should standards be set and met?: On the allocation of regulatory power in a federal system. BE J. Econ. Anal. Policy 10 (1).
Luca, D., Modrego, F., 2021. Stronger together? Assessing the causal effect of intermunicipal cooperation on the efficiency of small Italian municipalities. J. Reg. Sci. 61 (1), 261–293.
Matula, D.W., Sokal, R.R., 1980. Properties of gabriel graphs relevant to geographic variation research and the clustering of points in the plane. Geogr. Anal. 12 (3), 205–222.
Moreno-Monroy, A.I., Schiavina, M., Veneri, P., 2021. Metropolitan areas in the world. Delineation and population trends. J. Urban Econ. 125, 103242.
Muller, C., 2018. Heterogeneity and nonconstant effect in two-stage quantile regression. Econ. Stat. 8, 3–12.
Muller, S., Wilhelm, P., Haase, K., 2013. Spatial dependencies and spatial drift in public transport seasonal ticket revenue data. J. Retail. Consum. Serv. 20, 334–348.
Openshaw, S., 1973. A regionalisation program for large data sets. Comput. Appl. 3/4, 136–147.
Openshaw, S., 1977. A geographical solution to scale and aggregation problems in region-building, partitioning and spatial modelling. Trans. Inst. Br. Geogr. 459–472.
Openshaw, S., Rao, L., 1995. Algorithms for reengineering 1991 census geography. Environ. Plan. A 27 (3), 425–446.
Pettie, S., Ramachandran, V., 2000. An optimal minimum spanning tree algorithm. In: Montanari, U., Rolim, J.D.P., Welzl, E. (Eds.), Automata, Languages and Programming. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 49–60.
Porcelli, F., Vidoli, F., 2020. A comprehensive model for the evaluation of standard expenditure needs and standard level of local services. Local Gov. Stud. 46 (5), 734–762.
Postiglione, P., Andreano, M.S., Benedetti, R., 2013. Using constrained optimization for the identification of convergence clubs. Comput. Econ. 42, 151–174.
Postiglione, P., Benedetti, R., Lafratta, G., 2010. A regression tree algorithm for the identification of convergence clubs. Comput. Statist. Data Anal. 54, 2776–2785.
Reschovsky, A., 2006. Compensating local governments for differences in expenditure needs in a horizontal fiscal equalization program. In: Shah, A. (Ed.), Local Governance in Industrial Countries. Public Sector Governance and Accountability Series. The World Bank.
Reschovsky, A., 2007. Compensating local governments for differences in expenditure needs in a horizontal fiscal equalization program. In: Boadway, R., Shah, A. (Eds.), Intergovernmental Fiscal Transfers: Principles and Practice. World Bank.
Revelli, F., 2006. Performance rating and yardstick competition in social service provision. J. Public Econ. 90 (3), 459–475.
Rey, S.J., Janikas, M.V., 2005. Regional convergence, inequality, and space. J. Econ. Geogr. 5 (2), 155–176.
SOSE, 2020. Aggiornamento e Revisione della Metodologia dei Fabbisogni Standard dei Comuni Per Il 2021, Nota Metodologica Approvata dalla Commissione Tecnica Per I Fabbisogni Standard Il 30 Settembre 2020. Technical Report, https://www.mef.gov.it/ministero/commissioni/ctfs/index.html.
Tiebout, C., 1956. A pure theory of local expenditures. J. Polit. Econ. 64 (5), 416–424.
Ting, S.K., Dollery, B., Villano, R., 2014. Administrative scale economies in local government: An empirical analysis of sabah municipalities, 2000 to 2009. Urban Stud. 51 (13), 2899–2915.
Toussaint, G.T., 1980. The relative neighbourhood graph of a finite planar set. Pattern Recognit. 12 (4), 261–268.
Vidoli, F., Fusco, E., 2018. Level of services, spatial dependence and allocative efficiency in local governments. Local Gov. Stud. 44 (6), 848–873.
Vidoli, F., Pignataro, G., Benedetti, R., 2022. Identification of spatial regimes of the production function of Italian hospitals through spatially constrained cluster-wise regression. Socio- Econ. Plan. Sci. 101223.
Vidoli, F., Quintiliani, F., Ivaldi, G., Marinuzzi, G., Porcelli, F., Tortorella, W., 2024. Do municipal unions improve cost efficiency for the social function? A quasi-experimental endogenous stochastic frontier approach. J. Reg. Sci. 64 (2), 308–332.
Yang, H.-C., Bradley, J.R., 2021. Bayesian inference for big spatial data using non-stationary spectral simulation. Spat. Stat. 43.
Zouhar, Y., Jellema, J., Lustig, N., Trabelsi, M., et al., 2021. Public Expenditure and Inclusive Growth-A Survey. IMF Working Papers WP/21/83, International Monetary Fund.