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Spatial heterogeneity in non-parametric efficiency: an application to Italian hospitals

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Abstract

This paper introduces a new empirical procedure for the estimation of hospitals' technical efficiency in presence of spatial heterogeneity. We propose a methodology that allows treating the spatial heterogeneity independently of a predetermined reference to administrative borders. We define geographical spatial regimes, characterised by spatial proximity and homogeneity of relevant demand characteristics, within which to assess the efficiency of hospitals. The methodology has then been tested on a large sample of Italian hospitals, for which their production efficiency has been assessed within homogeneous demand areas.

Keywords: Productive efficiency, Conditional non-parametric efficiency, Spatial heterogeneity, Health sector

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1. Introduction

The measurement of efficiency in healthcare through the estimation of production and cost frontiers, particularly in the hospital sector, is quite widespread by now. See Kohl et al. (2019) for a recent survey of DEA studies on hospital efficiency.

One of the general concerns in the frontiers analysis of efficiency is related to the heterogeneity within the set of units employed as benchmarks. A significant portion of this heterogeneity is generally related to what are generally referred to as "environmental" or "contextual" variables, relative to health status and to the demand for health care faced by different healthcare units, as well as to characteristics of the market and of the regulatory context (see, among others, Rosko et al., 2017; Hafidz et al., 2018).

An important dimension of heterogeneity, which is gaining interest in the healthcare field as well as in other fields, is what can be referred to as spatial interaction, which allows considering issues that go beyond the mere geographic characterisation of contextual factors. There are, for instance, studies on the role of competition in healthcare that develop a theoretical and empirical analysis of the spatial interactions and feedback mechanisms between providers (see, among others, Spielman and Yoo, 2009; Gravelle et al., 2014; Brekke et al., 2011; Longo et al., 2017). Furthermore, the spatial analysis has developed into the consideration of spatial patterns and dynamics; in a study on the determinants of hospital admissions, Bech and Lauridsen (2008) (p. 51) state: "*these determinants may, however, not be randomly* *distributed across the geographical units, but may have an underlying spatial patterns. A non-random underlying spatial pattern may if ignored bias the significance of the determinants and invalidate conclusions*".

In other terms, the contribution of spatial analysis is in eliciting an heterogeneity, related to spatial patterns and interactions, which is not covered by observable contextual factors. However, it also needs to be considered that it is well possible that the pattern underlying the spatial "*interactions and feedback mechanisms*" cannot be univocally traced back to the (however identified) administrative clusters. Moreover, spatial patterns may also be the reflection of unobserved phenomena, which reinforces the lack of correlation with the administrative patterns relevant for the management of healthcare services. A recent paper by Amaral-Garcia et al. (2019) provides an example of spatial dependence, not correlated to observable factors of straightforward relevance for healthcare. The authors show a correlation between the geographical pattern of diffusion of the broadband Internet access with an increase in C-section rates, which is explained by the differential access to online information of first-time mothers living in areas with a broader Internet coverage.

There are now several works dealing with these latter issues, when analysing the behaviour of production units as linked to spatial factors, which can go under the heading of the so called spatial heterogeneity.

In terms of empirical analysis, spatial heterogeneity means that the spatial process may be not uniform over space implying estimates that present insta-

bility in *(i)* the mean, *(ii)* in the variance or *(iii)* in both. More specifically, instability in the mean implies local clustering of the values of a spatial variable. For instance, in the case of parameter instability, regression coefficients may follow a number of what are sometimes called *spatial regimes*, such as North-South or centre-periphery patterns (Brunsdon et al., 1996; Páez et al., 2002). It should be noted that the term spatial regime should not be understood as a perfect synonym of "cluster"; more precisely, the term "regime" is linked to the production function underlying the spatial process. The identification of different spatial regimes, in a sense, is equivalent to estimating different production (functional) regimes.
As Billé et al. (2018) point out, the spatial heterogeneity has been recently accounted for an increasing number of methodological papers (Andreano et al., 2017; Postiglione et al., 2010, 2013). Interestingly, it emerges that, specifically in the context of stochastic frontier models, distinguishing between heterogeneity and inefficiency is still an open problem (Amsler et al., 2016; Kumbhakar et al., 2014).

The objective of this paper is to provide an estimation of the technical efficiency of Italian hospitals, dealing with their heterogeneity, characterised in terms of spatial pattern. This analysis can be extended to any type of production units, either oriented to profit making or not. Technical efficiency is in fact instrumental to a better achievement of whatever goal pursued by producers. While the hospitals' technical efficiency is estimated through Data Envelopment Analysis (DEA), the main novelty of the paper, at least in terms of the application of the methodology to the healthcare sector, lies in the treatment of the spatial heterogeneity. More precisely, we depart from current approaches that incorporate heterogeneity through the use of contextual factors (in section 3, we extensively provide analytic details of these approaches). Differently from the conditional efficiency approach, we do not evaluate an exact relationship between the combinations of inputs and outputs of the different hospitals and a set of contextual factors connected with each hospital by "predetermined" location criteria (*e.g.* the value of the selected factors for the city where the hospital is located). We carry out a spatial identification of subsets of hospital peers, to perform the efficiency estimation of hospitals within each subset they belong to. As in Vidoli and Canello (2016), we adapt the robust order-m models by using a spatial criterion to identify the local peers for each hospital. Using the *Skater* procedure (Spatial K'luster Analysis by TreeEdgeRemoval, Assuncao et al., 2006), we combine the spatial dependence of the hospitals (in terms of the contextual factors of the conditional efficiency approach) with the spatial proximity of peers. We then build up clusters of hospitals using analytical regionalisation methods (also known as spatially constrained clustering, Murtagh, 1985; Duque et al., 2007) that are "*unlikely to have occurred by chance*"(Knox, 1989). Altogether, we identify 9 spatial regimes, each one of them including not less than 60 hospitals and we run a conditional order-m estimate of technical efficiency within each with appropriate sensitivity analyses considering different number and configurations of S, the physical space within each unit.

The remainder of the paper is organised as follows. In section 2 we present a summary of some relevant institutional characteristics of the Italian National Health Service (NHS) to provide a further motivation of our methodology and its application to Italian hospitals. In section 3, we describe our empirical strategy, and in section 4 we present our results. Section 5 is devoted to concluding remarks on the main contributions of the paper.

2. The institutional setting of the Italian National Health Service

The Italian NHS has been characterised, since the early Nineties, by a significant degree of regional decentralisation. Each Region has the power of organising the delivery of services to its residents, according to the objectives of the national health plan and ensuring the delivery of a nationally uniform benefits package (the so-called "*Essential levels of medical care*"), through Local Health Authorities (LHAs) and a network of public and private accredited providers. At the local level, LHAs are run by managers who are responsible for planning health care activities and for organising local supply according to population needs. They also are responsible for guaranteeing quality, appropriateness and efficiency of the services provided and are obliged to guarantee equal access, the efficacy of preventive, curative and rehabilitation interventions and efficiency in the distribution of services; The Legislative Decrees 446/1997 and 56/2000 imposed the transfer of the

NHS funds from the central to the regional level. Thus, it reinforced the autonomy of the regional health departments to align funding and spending powers. The regional governments became accountable for their health deficits.

The Italian case is, therefore, quite interesting since the now long-lasting history of decentralisation has marked a differential evolution of regional healthcare systems regarding rules, organisation of supply and financial and health outcomes. These differences, being the outcome of institutional differentiation, may well configure what Bech and Lauridsen (2008) refer to as a non-random spatial pattern that affects the differences in the relevant determinants of the production efficiency of Italian hospitals in each region. In dealing with spatial heterogeneity, however, it needs to be considered, again following Bech and Lauridsen (2008), that the organisation of the provision of services in one region may exert its influence beyond its borders. This is not far from being true in Italy because of the very different characteristics of Italian regions in terms of population and territorial size and of economic conditions, which favour the cross-regional interactions in the demand and supply of services. Moreover, the principle of free choice of services over all the national territory allows patients to move to whatever region they deem appropriate to satisfy their health needs. At the same time, the regional administrative borders are not always representative of clear-cut different historical patterns of economic and social development, so that some of the relevant observable and not observable factors that may affect healthcare providers' efficiency operate within clusters not coincident with these boundaries.

A large number of studies have examined healthcare efficiency in Italy with a variety of objectives, methodologies, and results. One of the earlier papers, by Cellini et al. (2000), offered a general picture of the technical efficiency of Italian hospitals and its determinants, in the aftermath of the crucial reforms of the Italian NHS in the early Nineties (see also Fabbri, 2003 and Barbetta et al., 2007). Unexploited economies of scale are a recurrent theme (Grassetti et al., 2005; Giancotti and Mauro, 2015), as well as the analysis of the efficiency of different providers such as private hospitals, public hospital trusts - Aziende Ospedaliere (AO), public hospitals directly managed by LHAs - Presidi Ospedalieri (PO), etc. (Barbetta et al., 2007; Daidone and D'Amico, 2009). In a recent paper, Cavalieri et al. (2018) examine how the efficiency of Italian hospitals is affected by the regional variations of the per case payment system. To the best of our knowledge, no effort has been devoted so far in analysing efficiency in terms of spatial heterogeneity, apart from a recent work by Cavalieri et al. (2017), which examines the spatial interdependence of Italian hospitals' efficiency. The novelty of our approach is that it provides an estimation of the efficiency of Italian hospitals, using homogeneous and contiguous territorial spatial regimes, as previously described.

3. Empirical strategy

The traditional non-parametric framework for technical efficiency analysis can be described by considering a production technology characterised by a set of inputs $x \in \mathbb{R}^p_+$ that are used by a Decision Making Unit (DMU) to produce a set of outputs $y \in \mathbb{R}^q_+$. Following the approach originally conceived by Debreu (1951) and Farrell (1957), the efficiency scores for a given production scenario $(x, y) \in \Psi$, where Ψ is the production set, can be defined in terms of the minimum amount of inputs potentially usable as follows:

$$\theta(x, y) = \inf\{\theta | (\theta x, y) \in \Psi\}. \tag{1}$$

One of the most problematic aspects concerning the non-parametric specification is the extreme sensitivity to outliers; to overcome this problem, Cazals et al. (2002) and Daraio and Simar (2005) proposed a non-parametric estimator of the most robust frontier to extreme and abnormal values. Given a sample of m random variables with replacement $S_m = \{\mathbf{Y_i}\}_{i=1}^m$ drawn from the density of $\mathbf{Y}$, the random set $\widetilde{\Psi}_m$ can be defined as:

$$\widetilde{\Psi}_m = \bigcup_{j=1}^{m} \{(\mathbf{x}, \mathbf{y}) \in \mathbb{R}^{P+Q}_+ | \mathbf{X} \leq \mathbf{x}, \mathbf{Y_j} \geq \mathbf{y}\}. \tag{2}$$

This specification limits the effect of outliers and measurement errors, as the single unit is not compared to the entire domain, but rather to a subset of peers of size m.

The treatment of outliers, however, deals with the heterogeneity representative of (somehow extreme) differences in the volume of inputs and outputs of the different productive units, but it does not deal with the heterogeneity arising from differences in relevant contextual factors not directly connected with their production choices. To overcome this shortcoming, Daraio and Simar (2007b) proposed an extension to convex non-parametric models, while Jeong et al. (2010) and Badin et al. (2012) proved the consistency and the asymptotic properties of different conditional efficiency estimators.
In analogy with the traditional Farrell's input-oriented efficiency score defined in equation (1), the conditional input efficiency measure can be defined as:

$$\begin{aligned} \widehat{\theta}(x, y|z) &= \inf\{\theta | (\theta x_0, y_0|z) \in \Psi\} \\ &= \inf\{\theta | H(\theta x, y|z) > 0\}. \end{aligned} \tag{3}$$

where z is the set of exogenous contextual variables - the *factors behind the patterns* (Bartelsman and Doms, 2000) - that is assumed to affect firm-level efficiency, but as stated by Lovell (1993) it is the set "*over which the decision maker has no control during the time period under consideration*" as, for example, the regulatory environment, the quality of the workforce or the different access to technology.

It should be noted that in equation (3), the unobserved factors Z have to be identified ex-ante and characterised in terms of a predetermined geographic location of productive units (e.g the city, the region, the State where productive units are located). Factors Z are also supposed to be independent from the production process: therefore, this strategy does not allow to account for relevant information related to other potentially important factors, which left out of the model, since they are truly unobserved or difficult to be measured.

In an attempt to overcome this issue, Vidoli and Canello (2016) proposed to incorporate the spatial dependence into a non-parametric efficiency model by accounting for the spatial proximity of peers rather than evaluating the exact relationships between X and Y and a set of contextual factors Z: they propose an algorithm derived by the order-m model by using a spatial criterion to identify the local peers for each unit according to "*the dynamics, the structure and characteristics of the considered market*" (Daraio and Simar, 2005).

The modified optimisation problem can be formally expressed by introducing in the random set $\widetilde{\Psi}_m$, defined in equation (2), an additional constraint associated with spatial proximity to the unit i, as follows:

$$\widetilde{\Psi}_{m_i} = \bigcup_{j=1}^{m} \{(\mathbf{x}, \mathbf{y}) \in \mathbb{R}_+^{P+Q} | \mathbf{X} \leq \mathbf{x}, \mathbf{Y_j} \geq \mathbf{y}, j \in S_i)\}. \tag{4}$$

where S_i represents the physical space within which the unit i is compared with its peers; Vidoli and Canello (2016) proposed to estimate S_i according with a spherical criterion of estimated radius; although this criterion is simple in its application, it is assumed that *(i)* the peers' range of influence remains the same throughout the whole territory considered - that is homogeneity in the spatial point patterns is hypothesised - and *(ii)* the reference territory is spherical.

In this paper, we propose to estimate the technical efficiency of Italian hospitals according to the optimisation problem set in equation (4), but we build S_i in a less rigid way than Vidoli and Canello (2016). More precisely, we determine S_i (the set of local peer units) in the conditional efficiency estimate in such a way to define spatial regimes characterised by: *(i)* spatial proximity of hospitals, identified not by a uniform radius, but taking into account their actual spatial distribution. Proximity here can also be regarded as a proxy of unobservable variables influencing the spatial patterns of hospitals' efficiency; *(ii)* spatial similarity of values of selected observable variables representative of factors potentially relevant for hospitals' efficiency; *(iii)* a minimum number of hospitals assigned to each regime. The actual identification of spatial regimes, with these joint characteristics, follows the so-called *Skater* algorithm. Assuncao et al. (2006) propose to identify the proximity of the production units using a connected graph (a tree that contains all the vertices of the graph and contains only a subset of the arcs, *i.e.* only those needed to connect all the vertices with one and only one path) in which each unit is identified with a point (corresponding, in our case, to a hospital's centroid according to a geographical reference) and it is connected to the centroids of the nearby units via an edge (Figure 1(a)). In more technical terms, a connectivity graph is used to capture the adjacency relations between objects. In the graph, each object is associated with a vertex and linked by edges to its neighbours. The cost of each edge is proportional to the dissimilarity between the objects it joins, where we measure dissimilarity using the values of the attributes of the neighbouring pair. By cutting the graph at suitable places, we get connected clusters.

A graph designed in such a way is very complex to evaluate since each point is connected to a plurality of other neighbouring points: to limit this complexity, Assuncao et al. (2006) proposed to use the "*Minimum Spanning Tree*" (MST, Pettie and Ramachandran, 2000) algorithm that allows the connection among all the objects that have a minimum weighted distance eliminating the very different edges (Figure 1(b)). In this way, the baseline tree is simplified in such a way to eliminate any cycle and to guarantee the minimum possible total edge weight. It can then be considered, from an economic point of view, as the backbone of the connections/relations among hospitals. The Minimum Spanning Tree, therefore, allows us to describe hospital production as an interconnected and interdependent set, spatially constraining the production units, but without imposing ex-ante a specific geography.

<Figure 1>

The second stage of the *Skater* algorithm provides that, starting from the MST connected graph, the edges with the greatest dissimilarity in terms of the selected observable variables are progressively eliminated in order to obtain k spatial clusters (not connected graphs), characterised at the same time by the maximum internal homogeneity and by the maximum heterogeneity with respect to the other ones (like a k-means clustering). The number k

must be such that each regime includes a minimum number of hospitals, so as to make the subsequent efficiency estimation significant. Once defined the k regions, we undertake the non-parametric estimation of efficiency within each regime.

Finally, please note that the proposed two-step approach produces valid inference assuming that the clustering procedure is independent of inefficiency (which is the classical assumption of the nonparametric conditional methods, Witte and Kortelainen, 2008; Vidoli and Canello, 2016) or, in other terms the spatial structure is linked to a heterogeneous technology adoption (linked to economic external factors) among the groups. In a non-parametric framework, therefore, it was not possible to include interactions and/or feedback mechanisms among neighbour units as in the parametric ones.

4. Empirical analysis

4.1. Data, production model and environmental factors

The data used in this paper come from different sources. Data for the assessment of the hospitals' efficiency within each spatial regime are provided by the Italian Ministry of Health (specifically, the Department of Health care) and refer to hospitals' discharge, personnel and beds records. More precisely, data refer to an initial sample of 880 public acute hospitals (*Aziende Ospedaliere*, hospitals independent of local health authorities - AO; *Presidi Ospedalieri*, hospitals managed by local health authorities - PO; teaching, research and other public hospitals) and private accredited hospitals in 2010.

Hospitals have been geocoded via Google Maps API through their name and their city. A very good geographic approximation has been obtained since 767 hospitals have been identified - in terms of latitude and longitude - at the level of establishment, 33 at street level, 29 at locality level and only 51 at a higher level. After selecting data referring to hospitals geocoded with the same coordinates (either because Google provided the same address or because they are duplicate) and some cleansing of data (see paragraph 4.3), the sample reduces to 742 hospitals. The data for relevant environmental factors that potentially affect hospitals' efficiency refer to the information available for the year 2010 and are mainly provided by the Italian Institute of Statistics (ISTAT).

Furthermore, the data set includes information on different inputs and outputs usually considered in the literature on hospital efficiency (Hollingsworth, 2008; Kohl et al., 2019). Based on the availability of data in our sample of Italian hospitals, we consider three inputs and one output to describe hospital production technology.

As in many other papers on the estimation of hospitals' technical efficiency, we include the number of hospital beds as a proxy measure of capital. The labour inputs are measured by the number of full-time equivalent physicians and the number of full-time equivalent nurses.
As for the outputs, hospitals are recognised to provide different services, thus calling for a multiple output approach. However, as common in efficiency study on Italian hospitals (*e.g.* Cavalieri et al., 2018), due to the availability

of data, we restrict our analysis only to inpatients activities (*i.e.* the number of discharged patients and the number of inpatient days). It also needs to be noted that Italian hospitals are compelled to focus on inpatient activities, since it is deemed appropriate that outpatient visits are carried out by local health authorities in specific and less costly structures. Furthermore, even if it is an highly debated issue whether to consider the outcome of health-care provision in the assessment of technical efficiency, we did not include it since data for hospitals' outcomes (*e.g.*, risk adjusted discharge mortality and readmission rates) were available only for limited hospitals' subsamples.

Consequently, we focus, as a measure of output, on the number of discharged patients. Since discharges can be very different from one another, in terms of complexity of treatments provided and of the resources used for these treatments, as it is common in the literature, we use a weighted sum of discharged patients, where the weights are the ones connected with the Diagnosis Related Groups (DRG) classification. We use the weights of the national DRG system, since Regions are allowed to make variations with respect to this national system. By employing the weights of the national DRG system (Ministry of Health Decree of December 18, 2008), we are able to offset both inter- and intra-regional differences in tariffs for the same DRG. In such a way we provide a reasonable standardisation of inpatients hospital output across the different units.

Furthermore, in our opinion, the adoption of a single output measure reduces the degree of arbitrariness that is somewhat present in any choice of multiple output measures and provides a more fair comparison among hospitals. In fact, the only other available variable (*i.e.* the number of inpatient days) measures the same hospitals' activity and as showed by Cavalieri et al. (2018) does not significantly affect the efficiency assessment. Moreover, because the Italian regions use different tariff system that provides different incentives in term of patients' length of stay, using such a measure of inpatient activity we potentially introduce a bias in the efficiency estimates.

As for the variables used in the Skater procedure - point *(ii)* (see section 3) - to consider spatial similarity, we employed data on demand characteristics that affect hospital care. As previously mentioned, the data are mainly provided by the Italian Institute of Statistics (ISTAT) and refer to the information available for the year 2010; in particular - to bypass the limits linked to the provincial boundaries - these environmental variables have been calculated (for each hospital) as the sum of data of municipalities located at less than 30 km (or 100 km) from each hospital: this ensures that the demand is actually linked to the territory of reference, but at the same time does not represent regional or provincial administrative levels; in this way, the local demand factors do not correspond to the administrative levels and, therefore, are not directly linked to the operational choices (budget, levels of care, ...) that may have generated them.

Please note that the different radius of the contextual variables is due exclusively to the different nature of the demand variables (proximity services such as births, wide-ranging factors such as population seeking employment);

moreover, this different construction has been considered for greater precision and does not impact on the criterion of endogeneity in the construction of spatial regimes.

In particular, as a proxy for demand characteristics in the hospitals' catchment area, we employ the population density per square km, the number of newborns per 1,000 inhabitants, the total number of deaths per 1,000 inhabitants and the number of deaths for road accidents per 100,000 inhabitants. Then, we use the municipal average income (standardised between 0 and 1) estimated by the Tax Department of the Italian Ministry of Economy and Finance and the population in search of employment from the ISTAT Labour force survey that provides official estimates of employment and job seekers. Altogether, then, we consider variables able to identify spatial regimes with homogeneous demand characteristics in such a way to "neutralise" the heterogeneity of relevant contextual factors that may impact on the estimation of hospitals' efficiency. The selection of the variables is in line with the literature briefly summarised in section 1, while Table 1 presents the descriptive statistics of the variables used in the specification of the production function. The latter have been normalised for the population (except for income, for which we consider its average).

<*Table 1*>

4.2. The hospitals' spatial regimes

The empirical strategy, discussed in section 3, requires a preliminary identification of hospitals' spatial regimes by spatial proximity and spatial homogeneity, the latter in terms of the environmental variables represented in section 4.1. Hospitals' spatial regimes are representative of the S_i in equation (4), which is used to condition efficiency estimates, according to Vidoli and Canello (2016). As already mentioned in section 3, the approach we employ for getting S_i is related to the use of the *Skater* algorithm, and it is different from the one originally used by Vidoli and Canello (2016), based on a fixed and uniform radius. Preliminary to the presentation of the results of the *Skater* algorithm, we have evaluated the appropriateness of departing from Vidoli and Canello (2016) as far as the identification of S_i is concerned. For this reason, we have analysed the real locations (spatial points pattern) of hospitals on the territory as compared to the homogeneous random ones; Figure 2 shows two spatial points patterns: the first one (the left one) has been simulated generating a random points pattern containing independent uniform random points on the Italian observational window, while the second one shows the real spatial location of hospitals. More precisely, the Italian observational window has been calculated as the α-convex hull of a given sample of points ($\alpha = 0.5$) in the plane or as affirmed by Edelsbrunner et al. (1983) as "*subgraphs of the closest point or furthest point Delaunay triangulation*".

<Figure 2>

A marked difference between the two spatial points patterns can easily be noticed since the spatial concentration is much higher in some parts of the national territory than in other ones. Please see the Electronic Supplementary Material for a more specific discussion on this issue.

Therefore, the homogeneous demand areas using the *Skater* algorithm to condition the efficiency estimates have been identified.

We first proceed to the construction of the Minimum Spanning Tree, which is representative of the spatial proximity across hospitals (Figure 3). Even if the minimisation of the weighted distance of the MST algorithm needs to be balanced by close attention to avoid spurious connections, we decided to keep the hospitals located in Sardinia and their connections within our analysis set. We are aware that their connections with the mainland hospitals can be regarded as spurious and that the subsequent construction of spatial regimes and efficiency estimates may be affected by this issue, but we prefer to have a complete picture of the country's hospitals' efficiency.

<*Figure 3*>

Spatial proximity, as represented by the Minimum Spanning Tree, is the basis for the evaluation of spatial homogeneity and the construction of clusters. Within the *Skater* procedure, the selected environmental factors to evaluate the homogeneity of spatially neighbouring hospitals are used. We also impose a minimum size of 60 hospitals for each spatial regime, and a number of regimes equal to 9, balancing the need to have spatial regimes as more homogeneous as possible, in terms of the selected environmental factors, with the requirement of including, within each regime, an appropriate number of hospitals. Some robustness checks of our choice are provided in section 4.5.

The partition of homogeneous and contiguous territorial spatial regimes is then represented in Figure 4. Please note that the *Skater* procedure, being of a hierarchical type, allows to obtain more and more nested parts of the territory than the hierarchically superior ones; in this way it is possible to study the spatial regimes according to the desired level of specification.

<Figure 4>

The statistics by spatial regimes, reported in the Electronic Supplementary Material, provide a clear picture of the specificity of each regime. As for the environmental factors used for clustering the neighbouring hospitals in terms of spatial homogeneity, the noticeable difference in their mean values reflects a good heterogeneity among the hospitals of different spatial regimes while the standard deviation within each regime tends to be generally lower than the corresponding value for the entire sample, which is a signal that our procedure has clustered together hospitals with a reasonable degree of homogeneity. The statistics for the inputs and the output of hospitals show a clear partition of the country between the Northern and the Southern regimes.

4.3. Spatial conditional estimation of efficiency vs unconditional order-m and two stage conditional approaches

As mentioned at the end of section 3, once the spatial regimes have been identified, we carry out the assessment of technical efficiency of hospitals within each of the nine regimes. The proposed procedure starts with the estimation of the unconditional non-parametric technical efficiency, which provides the tool for identifying outlier observations.

The unconditional estimates is repeated twice to overcome the presence of strong out-of-scale data. In a first step, DEA and order-m measures are compared by means of a quantile regression, with $q = 0.95$, to select outliers, while, in a second step, after excluding the outliers, the relationship is estimated again and it proves to be more stable. The identified outliers are then excluded in the conditional efficiency estimation. Figure 5 shows the relationship between the two efficiency measures before and after the outliers selection.

<Figure 5>

Technical efficiency estimation for the hospital sector is, therefore, performed using the spatial conditional method proposed in equation (4) with S_i corresponding to the estimated spatial regimes. The results of the estimates are provided in Electronic Supplementary Material (Table 3 and 4) where estimates have been normalised [0,1] to make them directly comparable.

As a way to highlight the contribution of our methodology and results, we

also measured the technical efficiency of the hospitals in our sample with other two methodologies. First of all, we used the unconditional order-m approach (over the entire sample), so as to have a benchmark dealing only with the heterogeneity arising from the existence of potential outliers. Secondly, we employed the Simar and Wilson (2007) two stage procedure, which is representative of the approach generally used to deal with the heterogeneity arising from environmental factors and, therefore, can be regarded as one of the nearest alternatives to our approach. Please note that the fully non-parametric conditional order-m method has been tested too, but the relative estimates have not been satisfactory because of their low variability. Results are available upon request from the authors.
Simar and Wilson (2007) suggest to use a double bootstrap procedure in order to improve the statistical efficiency in the second-stage truncated regression since "*bootstrap methods provide the only feasible means for inference in the second stage*" (Simar and Wilson, 2011). This approach has quickly become a standard in the empirical efficiency analysis with very many applications (see *e.g.* Fragkiadakis et al., 2016; Perez-Urdiales et al., 2015) and it allows to evaluate the contribution of the single conditional variables to the efficiency estimation.

Table 2 shows the estimated coefficients in the truncated regression of the reciprocal of DEA scores on the exogenous conditional variables. The R rDEA package (Simm and Besstremyannaya, 2016) has been used to estimate the conditional 2-stages model; in this package the second level estimates are

expressed as the relation between the reciprocal of the DEA scores (distance function with the range from one to infinity) and the exogenous variables Z: this means that the sign of the coefficients is to be understood as inverse with respect to the DEA standard scores.
The results show both the difference between the first and the second stage β and the statistical significance of the variables Income and Road deaths mainly linked to the economic gap between the Northern and the Southern regions.

<*Table 2*>

Table 3 (Electronic Supplementary Material) shows the results of the application of the unconditional order-m and of the two-stage conditional methodologies, together with the results of our spatial conditional approach. Even if the efficiency scores of the unconditional order-m and of the two-stage conditional applications are computed on the overall sample, they are represented for each of our clusters. As for the comparison between our spatial conditional measures and the unconditional ones, Table 4 (Electronic Supplementary Material) and Figure 6 (displaying the geographical distributions of the two measures) clearly show that the two distributions look indeed quite dissimilar. The main statistics of our estimates are generally lower than the corresponding ones for the unconditional estimation: this is especially true for the hospitals belonging to the third quartile. Moreover, this differential effect of our estimation with respect to the unconditional one is quite relevant when we consider the hospitals located in those geographical areas

whose average is the highest in the unconditional estimation (*i.e.* spatial regimes 5, 6 and 7). In other words, it looks like our methodology tends to reduce the efficiency scores of the best performers with an effect also on the ranking of the different geographical clusters in terms of average efficiency of their hospitals, as well as on the relative distance between the best and the worst average scores. The difference between the results of the unconditional order-m and the spatial conditional estimations is not completely surprising, when one considers that the former methodology builds up the frontier over the entire sample and, therefore, tends to emphasise the evaluation of the best performers, while our approach considers different frontiers for spatially proximate and homogeneous hospitals. In such a way the best performers in the overall sample need not to be so good when benchmarked with a subset of the sample made up of other efficient hospitals. This effect can be clearly observed in Figure 7, where we consider the efficiency scores of the two approaches for the hospitals of the Lombardy region, that is the hospitals that are among the best performers over the all country.

<Figure 6>

<Figure 7>

As for the comparison between the results of our approach and the ones of the application of the two-stage conditional methodology (please refer to Tables 5 and 6 (Electronic Supplementary Material) where Q_Z, the ratio of conditional on unconditional efficiency score (Daraio and Simar, 2007a) is reported), first of all it can be noted that the latter tend to "magnify" the efficiency scores for all the hospitals, as expected. Again, our scores tend to be lower above all for the best performers in each spatial regime and for the hospitals located in the best regimes. Our approach avoids to compare hospitals similar in terms of environmental conditions but located in spatially different areas, confirming that spatial proximity is not a mere geographical issue, but it tends to represent "hidden" patterns that tend to affect the providers' production behaviour.

4.4. Spatial patterns and regional administrative borders

One of the main motivations of our work and, consequently, of our proposed efficiency estimation methodology, is that the spatial patterns of hospitals' efficiency need not be univocally linked to the administrative borders (in the Italian case, the regional ones). The spatial constraint on the efficiency estimation is, therefore, based on clusters, defined with respect to spatial proximity and homogeneity of hospitals. We then checked whether the differences across the spatial conditional efficiency scores are still linked with the regional location of hospitals, that is whether the specific institutional and socio-economic characteristics of each region are strong drivers of hospitals' efficiency even when it is estimated with respect to different territorial subsets. To answer this question, the regional average distribution has been compared with the spatial position of the individual units, respectively, with the non-conditional and conditional distribution efficiency using

the Syrjala test, "*based upon a generalisation* [for the spatial setting] *of the two-sample Cramer-von Mises test for a difference between two univariate probability distributions*" (Syrjala, 1996, p. 75). In this test, the null hypothesis provides that the two empirical spatial distributions are drawn from the same unknown distribution; with a certain degree of approximation, therefore, if the $p-value$ is greater than 0.05 then the two distributions cannot be said to be as different between them; the more the $p-value$ tends to zero the more the two distributions tend to be different in space.
It should be noted that we assume to observe the whole population and not a sample, namely the sample error is equal to zero. In addition, we also assume non-sampling error, which leads to have no problems of over or under coverage of the population. In other terms, we do not infer from finite populations, but from a superpopulation of which we have observed a realisation y.

The basic assumption is that while the non-conditional measures may be still dependent on regional factors (*i.e.* the two distributions in space are not so different), our spatial conditional measures should be independent.
The Syrjala tests confirm this assumption. While the spatial distributions of conditional order-m efficiency and the relative average ones are independent (test equal to $\psi : 0.005805537$, $p-value : 0.004$ based on 1000 simulations), the same cannot equally be affirmed for the spatial distributions of the order-m efficiency and the relative average ones (ψ : 0.008226907, $p-value$: 0.090 based on 1000 simulations). As a consequence, our methodology of

conditioning the efficiency estimates on spatial regimes based on hospitals spatial proximity and spatial homogeneity of relevant demand characteristics, is able to grasp all the regional differentials.

4.5. Sensitivity analysis

When point-based measures of spatial phenomena are combined into higher level aggregations, a source of statistical bias may arise from the aggregation criteria themselves. This source of bias, called Modifiable Areal Unit Problem (MAUP), may have a major impact on the conditional results, given that the chosen number k of spatial regimes substantially modifies the homogeneous territorial areas.

It is, therefore, mandatory to evaluate how our results change with a variation in the clustering parameter k. As suggested by Saisana et al. (2005, p. 308), we have focused "*on how uncertainty in the input factors propagates through the structure of the composite indicator and affects the values of the composite indicator*".

Different distributions of conditioned efficiency have been estimated. These distributions (Figure 8) are both strongly correlated and the percentage differences with respect to the chosen number of clusters ($k = 9$) are really small (in about $\pm 5\%$).

This result can be due to a plurality of causes: the most important is certainly the hierarchical nature of the clustering algorithm, but other more economic ones can be found in the expenditure constraints (and therefore indirectly on labour and capital resources) that differently impact on the Italian regions.

<Figure 8>

5. Concluding remarks

As emphasised in the Introduction to this paper, a crucial issue for the precision and reliability of information about efficiency, is the ability of the different methodologies for assessing efficiency to deal with the heterogeneity across the different providers, especially when arising from factors out of their control. Even if this may appear like a sort of "narrow" methodological issue, its policy relevance is evident if one considers the possibility of using the results of the efficiency assessment for devising actions aiming at reducing the eventual inefficiency of (some) providers.

The policy relevance of the methodological issue of dealing with heterogeneity is even stronger for those health systems that are decentralised. A wide heterogeneity has emerged in these systems, with several unsolved issues, as far as their capacity to deal with efficiency, as well as with equity, is concerned (Figueras et al., 2006). In Italy, the national level regulation jointly with the decentralised organisation of hospital provision did not result in an increasing pattern of efficiency nor allowed for a process of convergence in efficiency among regions. While convergence is a sensible policy objective, at the same time heterogeneity across regions needs to be carefully considered to avoid that it is regarded as merely due to the behaviour of providers.

In this paper, therefore, we have emphasised the notion and the role of spatial heterogeneity, which goes beyond the identification of environmental factors used to condition the assessment of efficiency of providers. The assessment of efficiency through the benchmarking method of frontiers, in a context characterised by spatial heterogeneity of providers, therefore requires to compare like with like. We believe that the approach to assess efficiency we propose in this paper is more consistent with the nature of spatial heterogeneity characterising hospitals more than other approaches. At least as far as Italy is concerned, restricting benchmarking to each spatial regime avoids to compare hospitals operating in very different geographic areas and, consequently, to overlook the sort of "hidden" spatial patterns that may influence the behaviour of providers. Ignoring these patterns, as discussed in section 4.3, leads to an overestimation of the efficiency of the best performers in the entire sample, above all when it happens, as it is the case of Italy, that they are "clustered" in some areas (see the case of Lombardy region).

A specific result for the Italian case is that our methodology confirms that the Southern part of the country lags behind the other geographic areas. However, our results clearly show that there is enough room for gains in efficiency also for hospitals located in the Northern area of the country.

Furthermore, our results confirm the hypothesis that the presence of different spatial production regimes is related to the existence of a variety of latent unobserved factors, which are closely related to the spatial location of the observed hospital more than to the administrative boundaries. This is not to say that the institutional factors are irrelevant and we are aware there are studies emphasising this issue (see, for instance, Atella et al., 2014). However, we checked whether the regional location of hospitals was still a driver of our efficiency results and we showed, in section 4.4, that conditioning the estimation of efficiency on our spatial regimes seems able to grasp all the regional differentials. This result seems to confirm the existence of spatial patterns, based on geographic proximity and on demand characteristics, which influence the behaviour of providers in a homogeneous way. Moreover, these patterns look to be stronger than the institutional influence, generally connected with the incentives and the constraints arising from regional policies, thus revealing some weaknesses of the decentralisation process in Italy. The "young" age of Italian regions joined, for a few regions, with their really small dimension (both in terms of space and population) can be considered as the likely reasons for the incomplete development of an effective government capability, above all when compared to the strength of some demographic, social and economic factors (observed and unobserved), which cannot be constrained within administrative borders. This asymmetry between the spatial and the institutional homogeneity surely poses a policy problem about the future role of regions in the government of the Italian health care system. Leaving aside any consideration about decentralisation itself (even if the political and institutional debate has recently witnessed an increasing number of sceptical voices about the benefits of decentralisation), are the current regions the right jurisdictions for an effective government of the Italian health care system?

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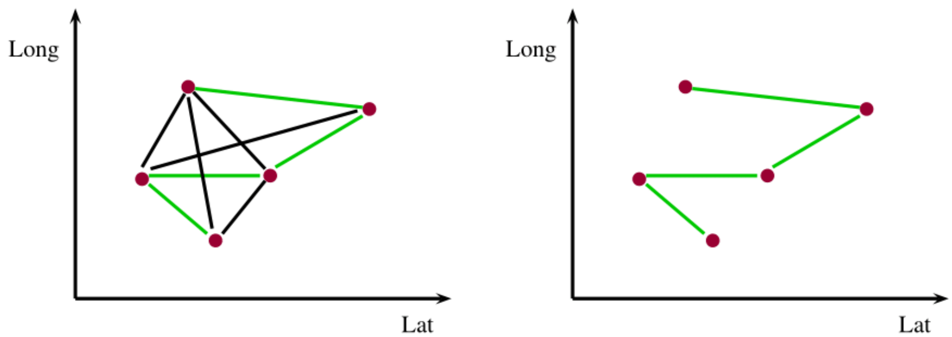
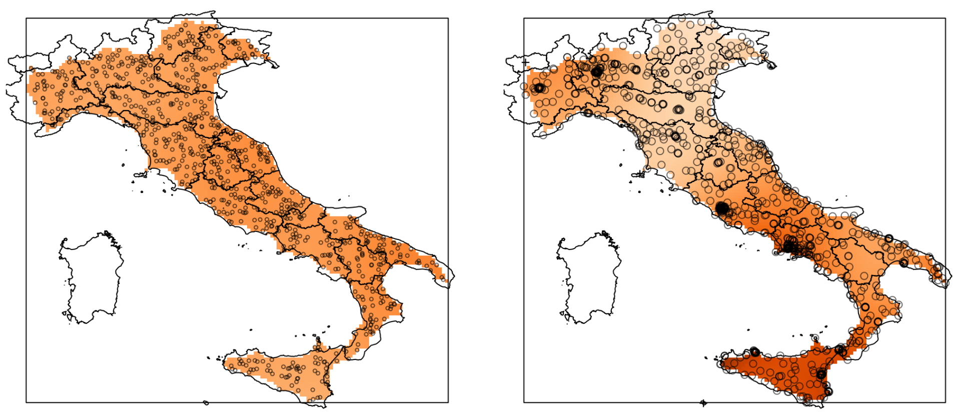


(a) *Connected graph.* (b) *MST reduced graph.*

Figure 1: Connected graph and Minimum Spanning Tree algorithm



(a) *Simulated homogeneous pattern.* (b) *Real pattern.*

Figure 2: Simulated homogeneous and real spatial point patterns

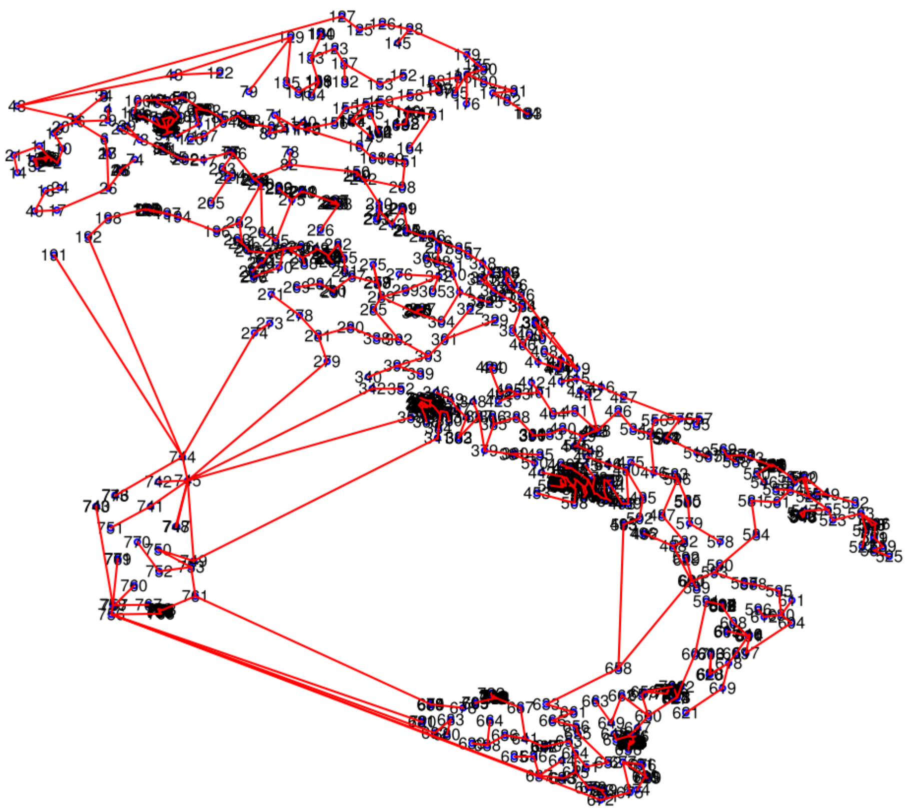


Figure 3: Minimum Spanning Tree for the Italian hospitals

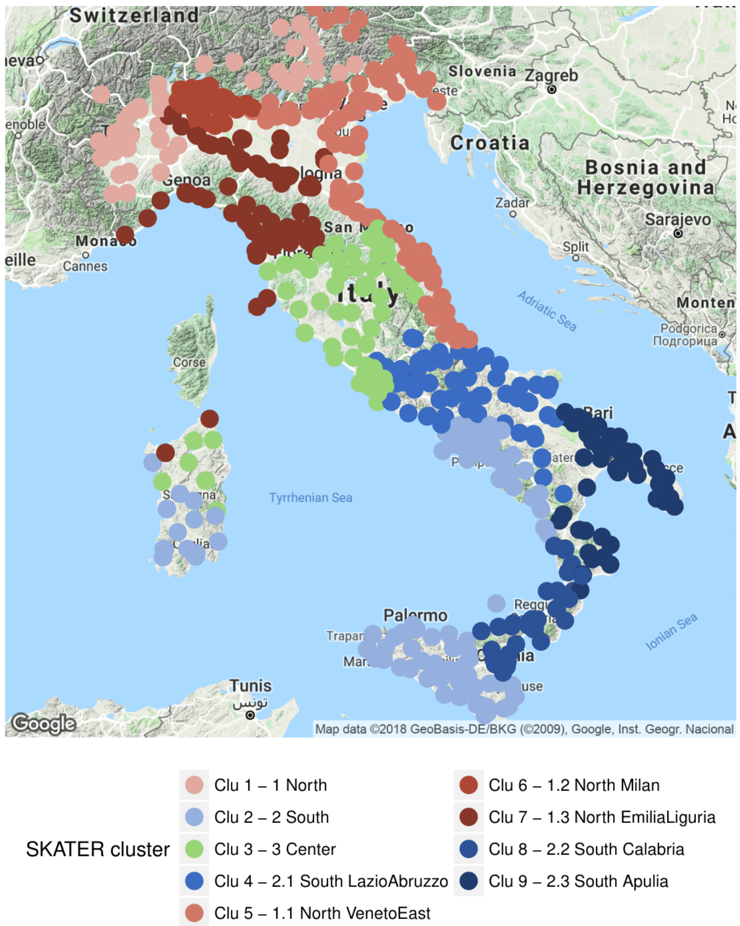
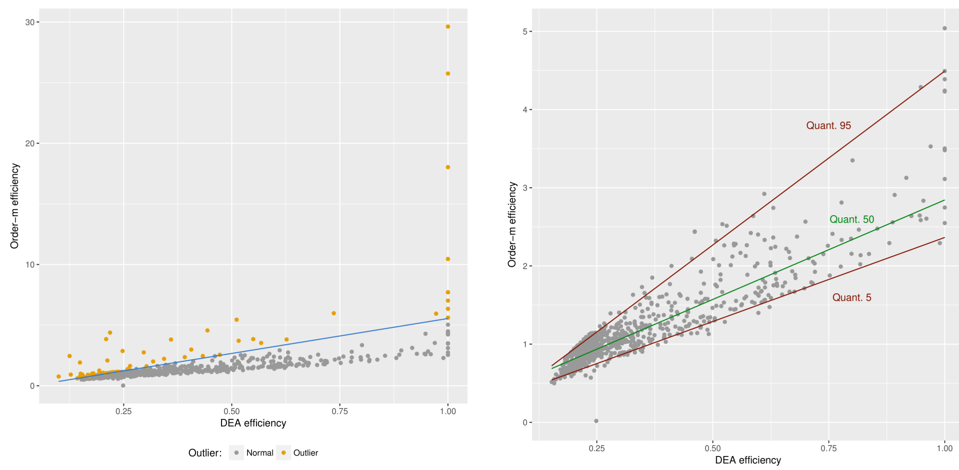
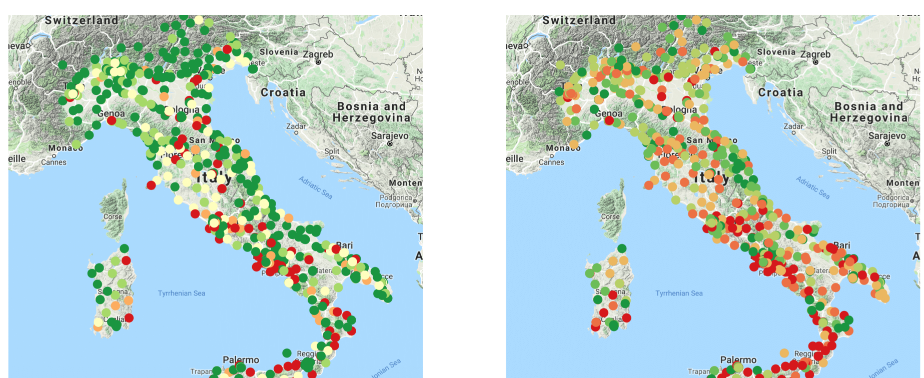


Figure 4: *Skater* spatial regimes, $k = 9$



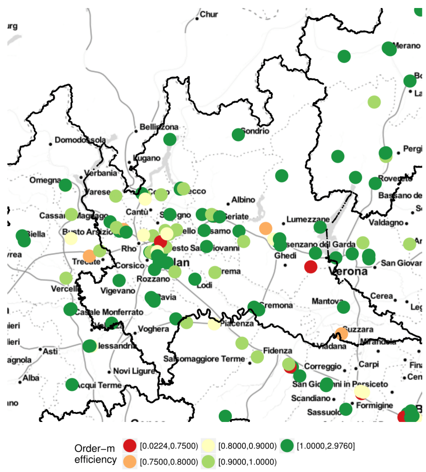
(a) *Before selection.* (b) *After selection.*

Figure 5: Out-of-scale data: outliers selection

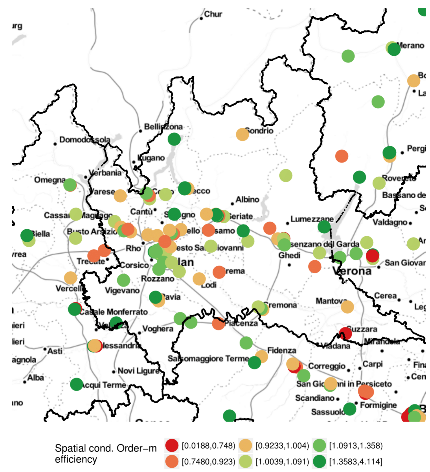


(a) *Unconditional order-m efficiency.* (b) *Spatial Conditional order-m efficiency.*

Figure 6: Unconditional and spatial conditional order-m efficiency

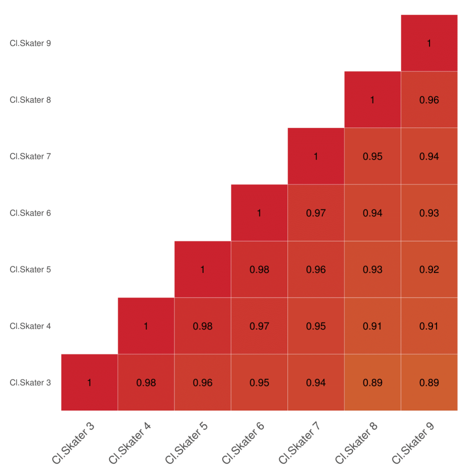


(a) *Unconditional order-m efficiency.*

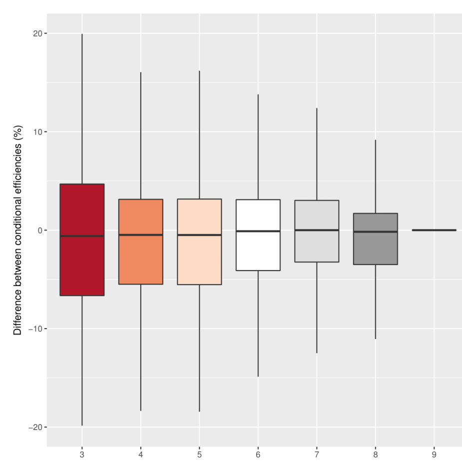


(b) *Spatial Conditional order-m efficiency.*

Figure 7: Unconditional and spatial conditional order-m efficiency - Lombardy Region



(a) *Correlations.*



(b) *Percentage differences boxplot.*

Figure 8: Uncertainty analysis for different k

Variable	Measurement	Radius (km)	Mean	SD
Input variables				
Bed	Total hospital beds	-	199.605	235.217
Phys	Total hospital physicians	-	124.955	145.550
Nurs	Total hospital nurses	-	270.942	367.694
Output variable				
Ric_pond	Weighted discharges	-	6,948.023	8,979.749
Environmental variables				
	Population density per km^2	30	521.235	587.274
	New born (*1000)	30	8.571	0.952
	Deaths (*1000)	30	1.604	1.918
	Income (min=0, max=1)	30	0.334	0.062
	Road deaths (*100000)	100	5.902	1.261
	Pop. search of employment (%)	100	5.601	2.208

Table 1: Descriptive statistics (year 2010)

Environmental variables	1^{st} loop	2^{nd} loop		
	β	β	CI Lower bound	CI Upper bound
Intercept	-32.473	-43.906	-70.658	-27.302
Population density per km^2	0.002	0.003	-0.002	0.010
New born ($*1000$)	-18.901	-23.306	-116.156	80.103
Deaths ($*1000$)	1.587	-0.545	-48.223	45.100
Income (min=0, max=1)	-37.125	-41.500	-81.342	-11.205
Road deaths ($*100000$)	-18.421	-20.227	-31.489	-15.713
Pop. search of employment ($*100000$)	28.115	31.018	-11.167	62.735

Table 2: Conditional efficiency (Second stage truncated regression, 95% confidence intervals)

Electronic Supplementary Material

Spatial points patterns:

Difference between real and simulated points patterns

Introduction

The difference between the real and simulated points patterns may be more rigorously evaluated through two specific measures (Baddeley et al., 2015): Ripley's reduced second moment function $K(r)$ - as a global measure (Figure 1, first row) - and the nearest neighbour distance distribution function $G(r)$ - as a local measure (Figure 1, second row) - for the simulated and the real points pattern.

Figure 1 (first row) shows Ripley K for the real case (left) and the simulated homogeneous distribution (right), showing a discrete inter-point dependence in the distribution of hospitals on the territory.

A more informative statistic, in this specific case, is the nearest neighbour distance distribution function $G(r)$. Figure 1 (second row) shows that for small radius (in other terms, locally) the cumulative distribution of the real case is very different from the homogeneous one; namely, there are very high concentrations of units for small distances and low concentrations for medium to large distances among hospitals, which does not make appropriate the use of Vidoli and Canello (2016) estimation method that assumes homogeneous points patterns.

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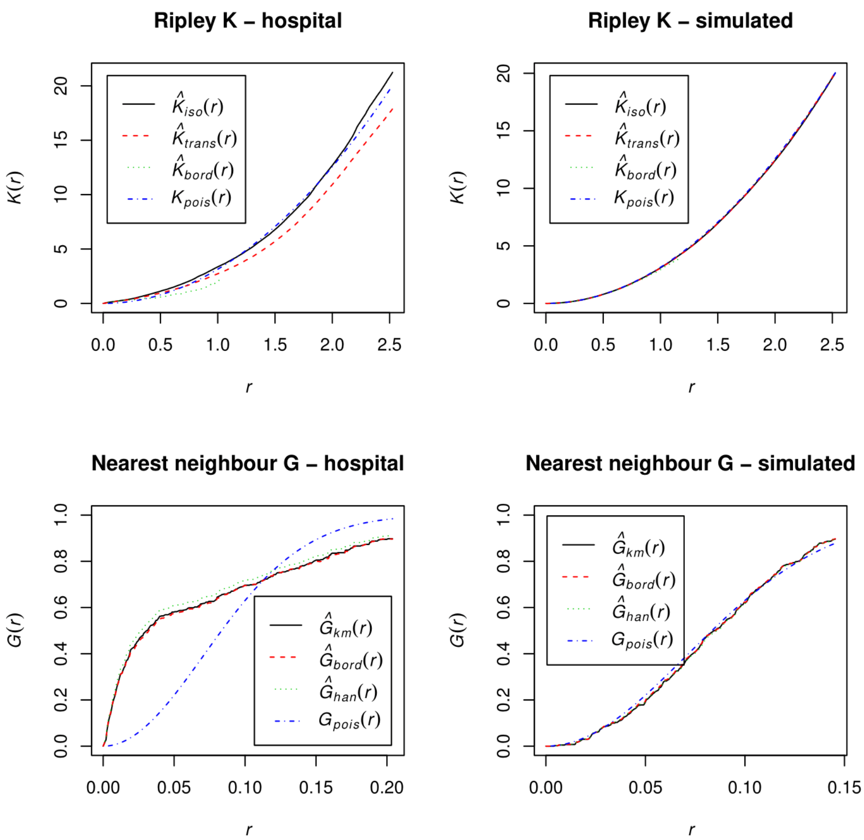

Figure 1: Ripley K and NN G for homogeneous and real spatial point patterns

Electronic Supplementary Material

Descriptive statistics by spatial regimes

Cluster	N	Ric Pond Mean	Ric Pond SD	Bed Mean	Bed SD	Doctors Mean	Doctors SD	Nurses Mean	Nurses SD
1 North	60	9096.8	7620.6	263.1	207.4	156.8	125.4	377.5	338.4
2 South	167	4026.1	4536.8	122.9	119.7	87.5	114.2	157.2	211.5
3 Center	87	5873.2	8725.8	165.2	218.5	112.8	136.7	225.6	301.1
4 South Lazio Abruzzo	64	5050.9	6082.4	153.5	172.0	88.8	91.6	205.2	223.3
5 North East Veneto	103	10302.3	10736.3	286.9	281.0	158.9	155.8	413.0	449.0
6 North Milan	59	13295.4	12718.9	371.3	319.4	227.0	185.9	508.9	548.6
7 North Emilia Liguria	80	11023.7	13033.0	306.7	344.9	196.8	213.0	432.8	542.3
8 South Calabria	63	2762.7	3507.0	94.4	111.2	68.0	91.2	96.6	131.2
9 South Apulia	59	6086.7	6285.0	170.2	154.2	104.3	92.1	218.2	203.6
All	742	7160.4	9098.8	205.5	238.1	128.7	147.2	280.1	372.2

Table 1: Input/output variables

Cluster	N	Density Mean	Density SD	Born Mean	Born SD	Death Mean	Death SD	Income Mean	Income SD	Road accidents Mean	Road accidents SD	Looking for a job Mean	Looking for a job SD
1 North	60	238.2196	143.4767	8.4934	0.9156	3.1062	2.1402	0.4053	0.0169	6.3016	0.8405	33.3165	4.6975
2 South	167	940.4476	931.9493	8.7372	1.1101	1.2435	2.0272	0.2692	0.0246	4.3682	0.7516	82.5680	3.2985
3 Center	87	400.9530	352.6115	8.7069	1.1227	1.3561	1.7233	0.3359	0.0423	6.6771	0.5628	45.3184	9.4536
4 South Lazio Abruzzo	64	118.4937	81.0612	8.0413	0.8671	3.7693	3.1126	0.2972	0.0187	5.8708	0.8189	64.3385	12.2901
5 North East Veneto	103	294.7979	120.0573	8.4762	0.7671	1.3436	1.0250	0.3809	0.0314	7.4108	0.5015	34.6371	6.3432
6 North Milan	59	1101.2886	362.3168	9.2099	0.1936	0.8887	0.4549	0.3969	0.0185	5.5325	0.1948	32.3508	0.6055
7 North Emilia Liguria	80	327.7079	138.9684	8.2446	0.9436	1.2782	1.4062	0.4116	0.0275	6.9383	0.8147	34.8077	7.0642
8 South Calabria	63	543.4967	439.2886	8.9032	0.9124	1.3685	1.0692	0.2875	0.0231	5.0813	0.4315	81.4067	4.0312
9 South Apulia	59	324.0679	165.1869	8.2645	0.4386	1.0032	1.0236	0.2804	0.0111	6.2200	0.8165	68.8121	2.8335
All	742	523.8970	588.8025	8.5787	0.9549	1.6061	1.9293	0.3339	0.0621	5.9247	1.2548	55.6573	22.0163

Table 2: Conditional variables

				Order-m					Spatial conditional efficiency					2-stage conditional efficiency		
Cluster	N	1 Quartile	Mean	Median	3 Quartile	SD	1 Quartile	Mean	Median	3 Quartile	SD	1 Quartile	Mean	Median	3 Quartile	SD
1 North	60	0.838	1.051	1.107	1.267	0.284	0.747	0.878	1.003	1.066	0.316	0.554	0.677	0.728	0.804	0.179
2 South	167	0.846	0.954	0.987	1.137	0.276	0.667	0.862	0.876	1.000	0.299	0.512	0.625	0.635	0.748	0.167
3 Center	87	0.891	1.020	1.001	1.144	0.257	0.881	0.965	1.000	1.076	0.291	0.556	0.660	0.673	0.750	0.152
4 South Lazio Abruzzo	64	0.868	0.988	0.997	1.178	0.274	0.821	0.907	0.968	1.023	0.292	0.570	0.646	0.656	0.752	0.150
5 North East Veneto	103	0.949	1.113	1.173	1.273	0.299	0.852	0.963	1.021	1.112	0.262	0.633	0.716	0.762	0.841	0.174
6 North Milan	59	1.013	1.166	1.192	1.362	0.325	0.950	0.964	1.003	1.073	0.212	0.603	0.699	0.726	0.861	0.196
7 North Emilia Liguria	80	0.939	1.109	1.150	1.296	0.303	0.675	0.848	1.000	1.090	0.360	0.604	0.704	0.759	0.837	0.185
8 South Calabria	63	0.699	0.858	0.910	1.020	0.294	0.691	0.830	0.807	1.002	0.287	0.475	0.550	0.564	0.646	0.157
9 South Apulia	59	0.922	1.061	1.087	1.200	0.265	0.793	0.872	0.982	1.022	0.293	0.587	0.681	0.691	0.801	0.159
All	742	0.869	1.029	1.034	1.217	0.296	0.747	0.898	0.990	1.054	0.297	0.550	0.660	0.680	0.797	0.174

Table 3: Unconditional, Spatial conditional and 2-stage conditional efficiency - summary

				Order-m					Spatial conditional efficiency					2-stage conditional efficiency		
Cluster	N	1 Quartile	Mean	Median	3 Quartile	SD	1 Quartile	Mean	Median	3 Quartile	SD	1 Quartile	Mean	Median	3 Quartile	SD
1 North	60	0.392	0.492	0.519	0.594	0.134	0.353	0.417	0.478	0.509	0.154	0.512	0.654	0.713	0.801	0.208
2 South	167	0.395	0.447	0.462	0.533	0.129	0.314	0.409	0.416	0.477	0.146	0.462	0.594	0.606	0.737	0.193
3 Center	87	0.417	0.478	0.469	0.536	0.121	0.419	0.460	0.477	0.514	0.142	0.514	0.634	0.649	0.739	0.177
4 South Lazio Abruzzo	64	0.406	0.463	0.467	0.552	0.128	0.390	0.431	0.461	0.488	0.142	0.530	0.618	0.630	0.741	0.174
5 North East Veneto	103	0.444	0.522	0.550	0.597	0.141	0.404	0.459	0.487	0.531	0.128	0.603	0.699	0.753	0.844	0.202
6 North Milan	59	0.474	0.547	0.559	0.639	0.153	0.453	0.459	0.478	0.513	0.104	0.568	0.679	0.711	0.867	0.228
7 North Emilia Liguria	80	0.440	0.519	0.539	0.608	0.143	0.318	0.402	0.477	0.521	0.176	0.569	0.685	0.749	0.839	0.214
8 South Calabria	63	0.326	0.402	0.426	0.478	0.137	0.326	0.394	0.383	0.478	0.140	0.420	0.507	0.523	0.618	0.182
9 South Apulia	59	0.432	0.497	0.509	0.563	0.125	0.376	0.414	0.468	0.487	0.143	0.549	0.659	0.670	0.798	0.184
All	742	0.407	0.482	0.484	0.570	0.139	0.353	0.427	0.472	0.503	0.145	0.506	0.635	0.658	0.794	0.202

Table 4: Unconditional, Spatial conditional and 2-stage conditional efficiency - Normalised estimate summary

Cluster	N	Spatial conditional Q_Z					2-stage conditional Q_Z				
		1 Quartile	Mean	Median	3 Quartile	SD	1 Quartile	Mean	Median	3 Quartile	SD
1 North	60	0.7448	0.8314	0.8281	0.9660	0.2798	0.6126	0.6461	0.6433	0.6854	0.0621
2 South	167	0.6448	1.1883	0.9110	1.1156	1.7653	0.6088	1.9654	0.6526	0.6927	10.3600
3 Center	87	0.8095	0.9907	0.9629	1.1218	0.3764	0.6160	0.6520	0.6551	0.6875	0.0756
4 South Lazio Abruzzo	64	0.7569	0.9898	0.9150	1.0907	0.4562	0.6302	1.2054	0.6564	0.6823	4.4562
5 North East Veneto	103	0.7692	0.9129	0.8672	0.9892	0.4551	0.6186	0.6488	0.6550	0.6782	0.0649
6 North Milan	59	0.7200	0.8972	0.8113	0.9181	0.3886	0.5608	0.6022	0.6052	0.6369	0.0721
7 North Emilia Liguria	80	0.6666	0.7707	0.7967	0.9115	0.3765	0.5986	0.6387	0.6530	0.6843	0.0780
8 South Calabria	63	0.7765	1.2836	0.9622	1.2574	1.5159	0.5809	2.0612	0.6359	0.6729	8.7080
9 South Apulia	59	0.7017	0.8455	0.8545	0.9318	0.3447	0.6239	0.6491	0.6522	0.6773	0.0795
All	742	0.7363	0.9936	0.8736	1.0421	1.0110	0.6059	1.1085	0.6498	0.6817	5.6970

Table 5: Ratio Q_Z for Spatial and 2-stage conditional efficiency - summary

Cluster	N	Spatial conditional Q_Z					2-stage conditional Q_Z				
		1 Quartile	Mean	Median	3 Quartile	SD	1 Quartile	Mean	Median	3 Quartile	SD
1 North	60	0.753	0.841	0.843	0.983	0.295	1.221	1.300	1.333	1.426	0.220
2 South	167	0.651	1.013	0.924	1.139	0.533	1.200	1.808	1.319	1.414	4.079
3 Center	87	0.822	1.009	0.980	1.145	0.391	1.217	1.322	1.346	1.425	0.194
4 South Lazio Abruzzo	64	0.767	0.977	0.926	1.092	0.412	1.201	1.907	1.339	1.408	4.801
5 North East Veneto	103	0.780	0.928	0.883	1.004	0.478	1.266	1.324	1.352	1.429	0.211
6 North Milan	59	0.732	0.912	0.827	0.935	0.402	1.088	1.212	1.221	1.351	0.246
7 North Emilia Liguria	80	0.673	0.779	0.812	0.930	0.395	1.175	1.298	1.332	1.443	0.236
8 South Calabria	63	0.777	1.116	0.981	1.280	0.571	1.049	2.284	1.255	1.375	6.113
9 South Apulia	59	0.711	0.857	0.870	0.949	0.359	1.274	1.324	1.321	1.403	0.188
All	742	0.746	0.947	0.888	1.065	0.458	1.197	1.551	1.322	1.420	2.992

Table 6: Ratio Q_Z for Spatial and 2-stage conditional efficiency - Normalised estimate summary