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Does neighbour’s grass matter? Exploring spatial dependent heterogeneity in technical efficiency of Italian hospitals

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Abstract

With respect to the other dimensions of hospital behaviour, studying the presence of interaction effects on efficiency involves the issue of which approach is most appropriate to incorporate the spatial dependence in the empirical efficiency model. Using a large sample of Italian hospitals, this paper explores the presence of spatial dependence in technical efficiency. To this purpose, we employ a Spatial Stochastic Frontier Analysis (SSFA) that allows us to robustly estimate the efficiency of each hospital while considering the presence of spatial dependence. Furthermore, we employ both standard spatial contiguity matrix and spatial matrixes exploring the idea of institutional contiguity. Overall, the results suggest an insignificant role for spatial dependence in the efficiency of Italian hospitals, regardless of the specific form of spatial dependence implicit in the weights matrix.

JEL Classification: C21; I11; D61.

Keywords: technical efficiency; hospitals; spatial dependence; SSFA.

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1. Introduction

There is an increasing interest in the health literature on the potential interaction effects among hospitals in different aspects of their behaviour. The underlying idea is that the behaviour of a given hospital may not be indifferent from that of other neighbouring hospitals. In this perspective, Mobley et al. (2009) estimate reaction functions in pricing behaviour of hospitals in the US, where prices are not fixed, and test strategic complementarity in prices through a spatial econometric approach. As for quality, the theoretical literature on hospital competition suggests that, under fixed price regulation, hospitals are induced to compete on quality with their rivals to attract more patients within the same local market (e.g., Gaynor, 2007; Brekke et al., 2011). In this respect, Gravelle et al. (2014) find that hospitals in the UK are strategic complements in many, even if not all, quality dimensions. In a similar perspective, Guccio and Lisi (2016) investigate whether the inappropriate behaviour of hospitals is affected by that of their peers, finding a significant presence of peer effects in Italy.

This paper explores the presence of spatial dependence in the efficiency behaviour of Italian hospitals. With respect to the other dimensions of hospital behaviour, studying the presence of interaction effects on hospital efficiency involves the additional issues of measuring the efficiency in the hospital sector (e.g., Mutter et al., 2011; Rosko and Mutter, 2011; Hollingsworth, 2012) and, most importantly, of which approach is most appropriate to incorporate the spatial dependence in the empirical efficiency model. Nonetheless, a few recent studies have investigated the presence of spatial dependence in hospital efficiency. Herwartz and Strumann (2012) implement a two-stage analysis where, in the first-stage, hospital efficiency is estimated by means of non-parametric (i.e. Data Envelopment Analysis, DEA) and parametric (i.e. Stochastic Frontier Analysis, SFA) frontier models and, then, standard spatial models (i.e. SARAR) are employed that account for spatial interdependence among hospitals. They conclude that, after the introduction of a prospective hospital reimbursement in Germany, the rise in competition for low cost patients has induced a negative spatial interdependence in hospital efficiency. In the UK, Longo et al. (2017) investigate the presence of spatial dependence in hospital efficiency by estimating different spatial models (i.e. SAR, SAC, cross-sections and panels) on several efficiency indicators, such as bed occupancy rate and cost indices for many hospital activities. As for the efficiency, their findings suggest the absence of spatial dependence among hospitals, consistently with their theoretical framework.

In this study, to the best of our knowledge, we employ for the first time in the health literature the Spatial Stochastic Frontier Analysis (SSFA) proposed by Fusco and Vidoli (2013), an integrated empirical approach that allows estimating the efficiency of each hospital, considering at the same time the potential presence of spatial dependence among hospitals. More specifically, the SSFA extends the standard error decomposition of the SFA model by adding a spatial autoregressive specification in the inefficiency term. As better discussed in the following, this approach has many important advantages with respect to two-stage approaches. In particular, when spatial dependence among decision making units (DMUs) is significant, the standard approaches to estimate the efficiency of DMUs (such as, DEA and SFA) have proved to generate biased results as they ascribe to the inefficiency term a part of the spatial dependence (e.g., LeSage, 1997). Therefore, two-stage efficiency models fail to provide a robust inference in the second-stage results. On the contrary, as the SSFA is immediately comparable with the corresponding SFA (i.e. without spatial autoregressive term), the former allows inferring robustly the presence of spatial dependence in hospital efficiency (e.g., Vidoli et al., 2016).

In general, a robust empirical approach seems to be especially important in exploring spatial dependence in hospital efficiency, as fairly any empirical finding could be deemed to be reasonable on the theoretical ground. On the one hand, it might be argued that, when prices are fixed and hospitals compete for low cost patients, those hospitals that are successful in attracting low cost patients use relatively less resources with respect to contiguous hospitals treating more complex patients, thus implying a negative spatial interdependence in hospital efficiency (e.g., Herwartz and Strumann, 2012). On the other hand, it might be also expected that, when public hospitals share the same health authority, being surrounded by many efficient hospitals could induce to be more efficient in the use of public resources, resulting in a positive spatial dependence. Finally, it is worth mentioning that rigorous theoretical models of hospital competition predict that, while hospitals are likely to be strategic complements in quality, they are independent in efficiency (e.g., Longo et al., 2017), consistently with an insignificant spatial dependence.

Looking at our study, the Italian National Health System (NHS) is a particularly interesting institutional context for investigating the presence of spatial dependence in hospital efficiency: in the last two decades, there has been an extensive devolution of healthcare responsibilities to regional governments (e.g., France et al., 2005). Therefore, significant differences exist in the regional health systems that, in turn, give rise to a large variability in the efficiency results of Italian hospitals (e.g., Barbetta et al., 2007; Cavalieri et al., 2016); under this perspective, in our empirical analysis such large variability in hospitals' behaviour could be exploited to disentangle the different sources of hospital production.

Our results are fairly consistent across different models and testing procedures, overall suggesting an insignificant role for spatial dependence in the efficiency of Italian hospitals, regardless of the specific form of spatial dependence implicit in the weights matrix. Therefore, in line with Longo et al. (2017), there does not seem to be a significant presence of spatial dependence in the efficiency behaviour of Italian hospitals.

The reminder of this paper proceeds as follows. In Section 2, we provide the methodological background for the study. Section 3 presents the dataset and the empirical strategy employed to test for the presence of spatial dependence in hospital efficiency. Then, in Section 4, we discuss the results of our empirical analysis. Section 5 concludes with some final remarks.

2. Methodological background

Spatial econometrics applications have progressively attracted the interest of researchers in health economics (Moscone and Tosetti, 2014) due to the importance of analysing the effects of geographical and institutional interdependencies on both the input and output variables of neighbouring units (e.g., local health authorities, hospitals, etc.). Most of the existing literature focuses on the relevance of spatial interactions in the case of health expenditures (Lippi Bruni and Mammi, 2015) and on the quality levels of health services provided by hospitals (Gravelle et al., 2014). The analysis of the influence of spatial patterns in the efficiency of hospitals, however, has received limited attention to date. In principle, the efficiency of a given hospital can be affected by the efficiency of neighbouring hospitals as a consequence of strategic interactions and common geographical and institutional factors (Longo et al., 2017). On policy grounds, moreover, investigating the role of spatial effects in explaining differences in efficiency across hospitals can be useful in order to evaluate the potential implications of hospitals' merging and antitrust policies, as well (Brekke et al., 2016).

Using the SSFA approach recently presented by Areal et al. (2012) and Fusco and Vidoli (2013), our work pursues two main objectives. First, we empirically test the presence of spatial heterogeneity in technical efficiency of Italian hospitals by comparing the results obtained from a standard non-spatial SFA with those generated by a SSFA. In particular, the SSFA framework employed in this paper allows for the decomposition of the inefficiency terms in a spatial autoregressive component (i.e. a spatial lag) and a unit-specific term and, more importantly, provides results that are comparable with those arising from a standard non-spatial SFA (Vidoli et al., 2016). This adds to the work of Longo et al. (2017), where spatial interactions in efficiency are modelled by applying spatial econometric models to indicators of efficiency for different units.[1] Second, our analysis complements previous findings in spatial health econometrics by introducing spatial dependence in the estimation of hospital efficiency in a more robust way. In fact, the application of the SSFA is found to be more consistent than the two-stage procedures used in Herwartz and Strumann (2012) for investigating spatial issues in technical efficiency. This is because the former approach provides efficiency estimates that are robust to the presence of spatial

[1] Differently from Longo et al. (2017) that use panel data, which are helpful for checking the consequences of time-varying effects, we apply the SSFA methodology to cross-section observations. For a discussion on the application of SSFA to panel data, see Chen et al. (2017) and Glass et al. (2016).

heterogeneity. In addition, we consider the Italian case where spatial characteristics have been already found to be relevant for the study of the health sector (Guccio and Lisi, 2016) as well as of other economic aspects (Tsionas and Michaelides, 2016).

We now start presenting the main features of the SSFA modelling approach that is used in the following empirical analysis. Specifically, for each unit of observation (i.e. the hospital), the Normal/Half-Normal spatial SFA model can be written as follows[2]:

$$\log(y_i) = \log\big(f(x_i;\beta_i)\big) + v_i - u_i =$$
$$= \log\big(f(x_i;\beta_i)\big) + v_i - \Big(1-\rho\sum_i w_i\Big)^{-1}\widetilde{u_i} \tag{1}$$

where y_i is the output of hospital *i*, x_i denotes the input vectors, f is a generic parametric function – in our case a Cobb-Douglas or a Translog function – $v_i \sim iid\ N(0,\sigma_v^2)$, $u_i \sim iid\ N^+\big(0,(1-\rho\sum_i w_i)^{-2}\,\sigma_{\tilde{u}}^2\big)$, $\widetilde{u_i} \sim N\big(0,\sigma_{\tilde{u}}^2\big)$. Observe that, v_i and u_i are iid with respect to each other and the covariates, as well. The inefficiency term u_i depends on the spatial lag parameter ρ and the spatial weights matrix *W*: that is, the level of technical efficiency of a given hospital can be influenced by the efficiency levels of the other hospitals $j \neq i$ on the basis of the particular neighbouring effects that are modelled through the elements of the spatial weights matrix. Simply put, in this framework spatial effects are modelled by introducing a spatial error autoregressive specification in the inefficiency term of the standard SFA error structure. For a sample of *n* DMUs, Fusco and Vidoli (2013) have shown that the log-likelihood of the relation in Eq. (1) reads as:

$$L(y|\beta,\lambda,\sigma^2,\rho) = 2\sum_{i=1}^{n}\left\{\phi\Big(\frac{\varepsilon}{\sigma}\Big)\left[1-\Phi\Big(\frac{\lambda\varepsilon}{\sigma}\Big)\right]\right\} \tag{2}$$

[2] Whenever possible we follow the notation used in Fusco and Vidoli (2013), where a more detailed discussion on the SSFA approach used in this paper can be found.

where $\sigma = \sqrt{\sigma_v^2 + (\delta(\rho))^{-2}\sigma_{\tilde{u}}^2}$; $\lambda = \frac{(\delta(\rho))^{-1}\sigma_{\tilde{u}}}{\sigma_v}$ and $\phi(.)$ and $\Phi(.)$ are the standard normal density and distribution functions, respectively. Eq. (2) can be then maximized with respect to the parameters by maximum likelihood.[3]

As underlined by Vidoli et al. (2016), the SSFA has three main advantages. First, by overcoming the potential biases present in standard non-spatial SFA (LeSage, 1997), it provides an estimation of technical efficiency that is robust to the presence of spatial effects. Second, the estimation of technical efficiency by the SSFA modelling approach does not suffer from the biases occurring in spatial applications based on two-stages SFA techniques (Wang and Schmidt, 2002)[4]. Third, SSFA results are comparable with those obtained from the application of standard non-spatial SFA; indeed, this aspect is especially important as our main objective is to assess the occurrence of spatial interactions in technical efficiency among Italian hospitals.

One additional advantage of the SSFA approach concerns the fact that it represents an ideal framework for distinguishing the presence of strong and weak spatial or cross-sectional effects (Bailey et al., 2016). On the one side, the introduction of regional fixed-effects in Eq. (1) makes it possible to control for the influence of strong spatial effects: that is, common (geographical and institutional) factors affecting technical efficiency of hospitals located in the same region. In this respect, the regional organization of the Italian health system and the presence of significant economic and social differences across the twenty regions suggest that common factors could play a significant role in shaping technical efficiency of hospitals (Atella et al., 2014; Cavalieri et al., 2016). On the other side, the parameter ρ within the inefficiency term captures residual or weak

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[3] For a different estimation procedure of Eq. (1), see Areal et al. (2012) that adopt a Bayesian procedure relying upon the combination of a Gibbs sampler and two Metropolis-Hastings steps.

[4] More specifically, the two-stage approach has serious drawbacks if the vector of efficiency variables is correlated with the vector of production function parameters, making the coefficient estimates of the production function biased (Wang and Schmidt, 2002). However, within the non-parametric frontier framework, Simar and Wilson (2007) propose a bootstrap truncated DEA two-stage approach that ensures a feasible, consistent inference for the parameters estimated. For a comparative analysis of the SFA two-stage estimates and DEA two-stage approach, see Schmidt (2011).

spatial effects in our sample: that is, the presence of spatial interactions across neighbouring units once common factors are controlled for. Therefore, the application of the SSFA approach allows taking into consideration the two main sources – common factors and neighbouring effects – of spatial interactions that can potentially occur when studying hospitals efficiency (Longo et al., 2017).

3. Empirical strategy and data

3.1. Empirical strategy

Since the '90s, a set of reforms aiming to promote regionalization and managed competition within the Italian NHS has widely shaped the hospital sector. The 20 Regional Health Authorities (RHAs) are now in charge of deciding how to organize and finance healthcare for their population. Particularly, they have full discretion of deciding whether to provide healthcare services beyond the mandatory standard benefit package defined at the central level (i.e. *Livelli Essenziali di Assistenza*).

The decision-making autonomy of the regions has concerned a number of important health issues, first of all the organizational set-up of regional healthcare systems. Among others, regional governments have been asked to decide: 1) on the number of local health authorities (LHAs) in which to divide their territory[5]; 2) whether to leave hospitals under LHA management, or grant them the status of trusts with full managerial autonomy (*Aziende Ospedaliere*, AO); 3) the degree of involvement of private providers. The regional choices have been reflected in a great heterogeneity of regional health models, especially concerning the mix of hospital care supply. Hospital providers can, thus, include public hospital units directly run by LHAs (*Ospedali a Gestione Diretta* or *Presidi Ospedalieri*), public hospital trusts formally independent of LHAs (i.e. AO), and accredited private hospitals (either for-profit or not-for-profit) that compete with the public hospitals in the delivery of services.

[5] The RHAs act through a network of geographic- or population- based LHAs, which are independent public entities with their own budgets and management.

Different regional healthcare models have resulted in marked geographical differences in terms of hospital size (as measured by hospital beds), volume of activity (as measured by the number of treated patients) and case-mix complexity (as measured by the case-mix index). Particularly, Graph 1 (left side) depicts the average number of beds per public hospital at regional level: the regions in the North of Italy show a larger average hospital size than those in the South and the two main Island. The picture does not change a lot when private accredited hospitals are also included (right side). In Graph 2, Italian regions are compared with regard to the average hospital (both public and private accredited) number of discharged acute patients (left side) and the average case-mix index (right side). With very few exceptions, the north-south divide continues to exist.

- GRAPH 1 about here –

- GRAPH 2 about here –

A number of empirical studies have investigated the efficiency of Italian hospitals, albeit with different scopes and methodologies. Among these, Barbetta et al. (2007) examine behavioural differences between public and private not-for-profit hospitals following the introduction of the DRG-based payment system in the Italian NHS. They estimate an output distance function and apply both parametric (COLS and SFA) and non-parametric (DEA) approaches to a balanced panel of 531 Italian hospitals between 1995 and 2000. The authors conclude that differences in economic performances between competing ownership forms are more the result of the institutional settings in which they operate than the effect of the incentive structures embedded in the different ownership forms. Daidone and D'Amico (2009) adopt a distance function approach and stochastic frontier techniques to analyse the impact of the productive structure and the level of specialization of hospitals on the technical efficiency of a 6-year panel of Italian hospitals. Controlling for environmental variables and hospital case-mix, they find that inefficiency is negatively associated with specialization and positively associated with capitalization. Cavalieri et al. (2016) employ a two-stage DEA, in which the estimated efficiency scores of Italian hospitals are regressed on different environmental variables, to investigate the impact of the use of DRG-based prospective payment systems on hospitals' efficiency.

Building on this literature, in our empirical analysis we start by estimating standard parametric frontier models (i.e., OLS, COLS, SFA) under different assumptions on the functional form of the production function (i.e., Cobb-Douglas and Translog) and testing for the presence of spatial dependence in efficiency by the Moran's I test. Then, we estimate the SSFA models to obtain hospital efficiency scores robust to the presence of spatial dependence, which allows inferring the significant presence of spatial dependence in hospital efficiency (e.g., Vidoli et al., 2016). As for the spatial weights matrix, we first consider a standard spatial contiguity matrix, and, then, check the robustness of the results with respect to other different spatial matrixes exploring the idea of institutional contiguity, which might be relevant in our context (Atella et al., 2014; Guccio et al., 2016). Specifically, the spatial contiguity matrix in our estimates is based on the Euclidean distance between hospitals. Therefore, we call $W \in R^{nxn}$ an Euclidean distance matrix (EDM) if there exist points $p_1, p_2, \dots, p_n$ (i.e. hospital locations expressed as latitudes and longitudes) such that:

$$w_{ij} = \left\| p_i - p_j \right\|^2 \text{ for } i, j = 1,2, \dots, n. \tag{3}$$

In particular, every EDM is a nonnegative symmetric matrix with zeros on its main diagonal, but not *vice versa*.

3.2. Data

The data used in this paper are provided by the Italian Ministry of Health (specifically, the Department of Healthcare) and refer to hospital discharge records and activity information. The final sample comprises cross sectional data on 866 hospitals, both public and private (for-profit and not-for-profit)[6], working

[6] To control for existing differences in the sources of funding between public and private hospitals, we restrict the analysis of the latter category only to those services covered by public funds (i.e. the number of beds accredited with the NHS and a proportional fraction of their personnel).

on behalf of the Italian NHS in the year 2010. Table 1 shows the composition of the sample by geographical area. Overall, the sample covers 66.8% of the total hospital discharges for acute patients in Italy in the year 2010 (i.e. 10.396.714 discharges). Most of the hospitals included in the sample are located in the South and the two main Islands of the country (49%), followed by the North (29%) and the Centre (22%). However, looking at the total number of discharges of acute patients, the previous picture is reversed: around 44% of discharges are placed in the northern regions while only 36% in the southern regions and 20% in the central ones. The latter geographical distribution is further confirmed by the average number of acute discharges by hospitals and, indeed, is consistent with the Italian reality where many small-sized hospital structures operate in the South and the Islands.

- TABLE 1 about here –

The dataset contains information on different inputs that are usually taken into consideration in the literature on hospital efficiency. Among these, the number of hospital beds is included as a proxy measure of capital. Labour inputs are measured by the number of full time equivalent personnel units (physicians, nurses, and others). As for the measurement of output, hospitals are recognized to provide highly different products in terms of quality and quantity, thus calling for a multiple output approach. However, frontier techniques are better suited to estimate efficiency when the product is homogeneous and one-dimensional (e.g., Daidone and D'Amico, 2009). This is because multiple output efficiency techniques require the estimation of a distance function that incorporates discretional choices regarding what type of outputs to include in the analysis and what output is to be used to normalize the others.

To overcome all these problems and to account for technology differences among units in the production of hospital care, we restrict our analysis only to acute patients and we employ a single output approach. This is computed in two steps. First, for each hospital the revenue is estimated in monetary terms by applying the national DRG system (Ministry of Health Decree of December 18, 2008) and the tariff agreement for interregional mobility (*Tariffa Unica Convenzionale*, TUC, 2012) to all discharged acute patients. By employing the national tariff system, we are able to offset both inter- and intra-regional differences in tariffs for the same DRG. Specifically, inter regional differences are related to the fact that each region is entitled to adopt either its own tariff system or the national one, while intra-regional differences refer to the possibility that regions differentiate tariffs according to the typology of hospital providers (e.g., public versus private; teaching versus non-teaching; etc.). A picture of the distribution of hospital monetary revenue by geographical area is provided in Table 2. Overall, revenue differences among geographical areas replicate those presented in Table 1 and concerning the total number of discharges of acute patients.

- TABLE 2 about here –

Second, to make easier the interpretation of the estimates of the production function, we transform the monetary hospital revenue dividing it by the base DRG point according to the TUC 2012 (2,049 euros). Therefore, our output variable measures hospital revenue in terms of DRG points[7]. Table 3 presents the descriptive statistics of the main variables used in the specification of the production function.

- TABLE 3 about here –

[7] Indeed, measuring output in terms of total virtual revenue would make hospitals homogeneous with regard to their choices of treating the patient in a day-hospital or inpatient setting. Otherwise, applying simple DRG weights would make those hospitals where the day hospital regimen is mostly used – for instance due to a favorable regional tariff system – appear as systematically more efficient than the others, simply because the DRG weights are the same but the day hospital treatment requires less inputs, *ceteris paribus*.

4. Results

4.1 Baseline efficiency estimates

A number of different functional forms are used in the literature to model production functions (e.g., Mutter et al., 2011; Rosko and Mutter, 2011; Hollingsworth, 2012). Among these, the Cobb–Douglas and the Translog functional forms are probably the most well-known. The Cobb–Douglas allows interpreting coefficients as output elasticities (i.e. covariates are all expressed in logs) and it is easy to interpret. However, its main drawback is that it assumes constant input elasticities and return to scale for all hospitals. In this regard, the Translog form imposes fewer restrictions on production and substitution elasticities, but it is susceptible to degrees of freedom problems and multicollinearity. Both Cobb-Douglas and Translog functions are linear in parameters and can be estimated using least squares methods. In this study, we employ the Cobb-Douglas form as the baseline specification and the Translog form as a robustness check[8].

As a first step of our analysis, we run a OLS regression with a log–log functional form in order to provide a simple test for the presence of technical inefficiency in the data. The general form of the Cobb-Douglas production function used in our cross-sectional one-output stochastic frontier model is as follows:

$$\ln (DRG\_W\_REVENUE)_{ij} = \beta_0 + \beta_1 \ln (BEDS)_{ij} + \beta_2 \ln (PHYSICIANS)_{ij} + \beta_3 \ln (NURSES)_{ij} + \beta_4 \ln (O\_PERS)_{ij} + \boldsymbol{\Sigma} \beta_j \, REGION_j + \varepsilon_i \quad (4)$$

$$\varepsilon_i = v_i - \mu_i \quad (5)$$

where i denotes hospital, j refers to region, $REGION_j$ is a vector of regional dummies, and ε is the composed error term. The latter have two components: v is an error term and μ is a vector of inefficiency terms with non-negative values.

[8] In the empirical literature there is a large debate on which functional form is the most appropriate. The Translog production function is generally recognized to be more flexible than the Cobb-Douglas one, though it can also result in incorrect efficiency results for observations that are not close to the mean scale (Kumbhakar and Lovell, 2000). Furthermore, the Cobb–Douglas specification allows interpreting coefficients as output elasticities as the covariates are all expressed in logs.

All the variables included in the model, except for the regional dummies, are in logarithms.

Results from OLS regression are reported in Table 4 for the specification without (1) and with (2) regional fixed effects. These are included to account for the potential effects of differences in regional regulatory contexts on hospital production, and are intended to control for the effects of common (geographical and institutional) factors affecting technical efficiency of hospitals.

- TABLE 4 about here –

Overall, the results confirm the validity of the Cobb-Douglas functional form. For both specifications, the intercept (though positive) and all covariates are highly significant (at the 1% level), the *R*-squared is high (around 0.86) and the first-order homogeneity condition of the production function in inputs is verified. Comparing the two specifications, regional fixed effects seem to play a relevant role in explaining the hospitals' production process as shown by both the joint significance of the *F*-test and the slightly lower AIC value.

- GRAPH 3 about here –

To check for the validity of our models' stochastic frontier specifications, we test the (negative) skewness of residuals. In Graph 3, the histograms of the OLS residuals of both our models are plotted compared to a normal density. The skewness test (Schmidt and Lin, 1984) does not reject the null hypothesis of no skewness but is not statistically significant. However, the M3T statistic suggested by Coelli (1995) provides highly statistically significant evidence of negative skewness for both models (-9.3929 and -9.6655, respectively). For both our models, Graph 3 also depicts the histograms of the corrected OLS (COLS) and corrected Median Absolute Deviation (CMAD) efficiency estimates. In both cases and for both models, the mean efficiency values are quite similar (between 0.25 and 0.28) and dispersions of efficiencies are not very reasonable.

To assess the technical efficiency of hospitals, an output-oriented stochastic frontier model is estimated[9] under the hypothesis of half normal distribution of residuals (Kumbhakar, 1990). As shown in columns (1) and (2) of Table 5, where a Cobb Douglas functional form is used to mimic the hospital production function (without and with regional dummies, respectively), the SFA parameters are quite similar to those arising from the baseline OLS model while the intercepts continue to be positive but slightly increase in absolute value. This is consistent with the fact that the production function has been shifted from the average values to efficient ones without affecting the relationship between output and inputs (Vidoli et al., 2016). Moreover, for both specifications, the highly significance (at the 1% level) of the likelihood ratio (LR) test confirms the goodness-of-fit of the SFA model. As a robustness check for these findings, we also use a Translog functional form that imposes less restrictions then the Cobb-Douglas one. The results from (3) and (4) of Table 5 further confirm the previous conclusions concerning the validity of the SFA model. Again, under both assumptions on the functional form, the SFA specification with regional fixed effects is proved to be slightly better than that without fixed effects. From Table 5, the estimates of the gamma parameter (γ)[10] range from 0.67 to 0.73, meaning that the variation in the composite error term is largely due to the inefficiency component. As for the mean efficiency score, it varies from 0.70 to 0.72, depending on the model and the specification. Therefore, there is room for around 30% average improvement in hospital output, keeping constant inputs and technology.

- TABLE 5 about here –

- GRAPH 4 about here –

[9] All estimates are performed with the R package 'ssfa' (Fusco and Vidoli, 2015).
[10] The gamma parameter (γ) can take values from 0 to 1. When the value is close to zero, all deviations from the frontier are attributed to noise. Instead, when the value is equal to unity, all deviations are caused by technical inefficiency of the DMUs.

Graph 4 displays histograms, the pairwise correlation matrix and the geographical distribution of the SFA efficiency estimates presented in Table 5. On the whole, the four histogram pictures look very similar with regard to the shape of their distribution, thus telling the same story. The covariance matrix further confirms that the distributions are highly correlated between them (r>0.9). Looking at the geographical distribution of the efficiency scores, in all the estimated models hospitals located in the Centre and North of Italy tend on average to be slightly more efficient than those operating in the South, also showing a lower dispersion of values around the mean.

4.2 Spatial Stochastic Frontier Analysis

Traditional SFA model assumes that the DMUs are mutually independent, thus ruling out the possibility of their performance being affected by neighbours' behaviours. To account for hospital efficiency interactions across space we perform some preliminary tests based on the global Moran's I statistic (Moran, 1950). To this purpose, a contiguity symmetric spatial weights matrix based on the Euclidean distance between hospitals is employed (see Section 3.1 for details). Graph 5 displays the global Moran's I statistic for the four SFA models presented in Table 5. The global Moran's I statistic is never statistically significant, implying no spatial autocorrelation between SFA efficiency estimates.

- GRAPH 5 about here –

Furthermore, a common visual tool to explore spatial data is the Moran's scatterplot, where the (standardized) values for each DMU on the x-axis are plotted against the respective spatial lag values on the y-axis. Graph 5 displays the Moran's scatterplots for the residuals of each of the SFA models in Table 5. The Moran's scatterplot allows identifying four different quadrants, each of which presents a different type of spatial association between a hospital and its neighbours. In the Graph, residuals are almost uniformly distributed in the four quadrants and mainly aligned along the *x*-axis. This distribution suggests neither positive nor negative spatial dependence for SFA residuals.

Then, we test the absence of spatial effects for our data by employing the SSFA approach firstly proposed by Fusco and Vidoli (2013). Therefore, by separating the spatial component from the individual efficiency of the DMUs, the SSFA allows us to estimate robustly the efficiency of each DMU and to test for the presence of spatial interactions in efficiency (Vidoli et al., 2016). The results from estimations of the previous four models are reported in Table 6, using an Euclidean distance-based spatial weights matrix. In all of the cases, the input coefficients are similar to those obtained from the SFA. Looking at the gamma parameter (γ) for each SSFA model, it is worth noting that they are fairly equal to those for the non-spatial SFA models in Table 5. This suggests that the spatial autoregressive component in the SSFA has not contributed a lot to explain the variance of hospitals' performance (Vidoli et al., 2016). Furthermore, the σ^2_{dmu} exhibit high values, further confirming that the inefficiency variance is almost entirely due to DMUs' specificities.

As a robustness check for our spatial estimates, we employ an extension of the Spatial Error Model (SEM; Anselin, 1988) to the SFA model, proposed by Pavlyuk (2015). More specifically, the SEM model allows for spatial correlation of the random term values. In the simplest first-order autoregressive case, the error term can be expressed as:

$$\varepsilon = \rho W \varepsilon + \tilde{\varepsilon} \tag{6}$$

where ρ is an unknown coefficient describing spatial heterogeneity, W is a spatial weights matrix and $\tilde{\varepsilon} \sim N(0_n, \sigma^2_\varepsilon I_n)$. The approach proposed by Pavlyuk, (2015) is simply a direct extension of the SEM model to stochastic frontier models that account for the presence of spatial heterogeneity:

$$\nu = \rho W \nu + \tilde{\nu} \tag{7}$$

Being the structure of spatial dependence expressed by a non-spherical error covariance matrix, OLS remains unbiased, but it is no longer efficient and the classical estimators for standard errors will be biased. Therefore, Maximum

Likelihood Estimation (MLE) is used in Table 6.[11] All in all, previous estimation results as well as main conclusions about the limited role of spatial effects in explaining the variance of DMUs' efficiency levels are confirmed.

- TABLE 6 about here –

4.3 Robustness checks

Thus far, in all our testing strategies for the presence of spatial dependence in efficiency we have emphasized the standard spatial contiguity as the form of interdependence among hospitals. However, one could reasonably argue that in our specific application the interdependence among hospitals might come from other social and/or institutional forces than the spatial proximity. For instance, it could be expected that sharing the same LHA might induce hospitals to pay attention to the efficiency behaviour of other hospitals under the same authority regulation. Therefore, to further test the presence of interdependence in the efficiency behaviour of hospitals, in the following we run two robustness checks by considering two different specifications of the spatial weights matrix. In particular, as a first robustness check, we specify the spatial weights matrix (not based on the geographical contiguity but) based on belonging to the same LHA, in order to test the form of interdependence discussed above. Specifically, the row-standardized spatial weights are as follows:

$$w_{ij} = \begin{cases} \dfrac{1}{n_{LHA} - 1} & if\ LHA_i = LHA_j \\ 0 & otherwise \end{cases} \tag{7}$$

where n_{LHA} indicates the total number of LHAs. In Eq. (4) the efficiency behaviour of hospitals is correlated with that of other hospitals under the same LHA regardless of the geographical contiguity, thus emphasizing the primary role of institutions in affecting hospitals' behaviour (Atella et al., 2014; Guccio and Lisi, 2016). Finally, we run a similar robustness check at the province level,

[11] All estimates are performed with the R package 'spfrontier' (Pavlyuk, 2016).

implying that the efficiency behaviour of hospitals is correlated with that of other hospitals within the same province.

Table 7 shows the results of our SSFA estimates with the spatial weights of Eq. (7) at the LHA level. Overall, compared to the previous results, fairly nothing changes both in the parameters of the production function and in the sigma parameters of the SSFA model. In particular, looking at the gamma parameters (γ) in Table 7, it can be seen again that they are fairly equal to those for the non-spatial SFA models in Table 5. As presented in Table 8, a similar picture can be seen also for the SSFA estimates with the spatial weights at the province level. Therefore, these robustness checks further support our conclusion of an insignificant role of spatial dependence in the efficiency behaviour of hospitals, regardless of the specific form of spatial dependence implicit in the weights matrix.

- TABLE 7 about here –

- TABLE 8 about here –

5. Concluding remarks

This paper explores the presence of spatial dependence in the technical efficiency of Italian hospitals. With respect to previous approaches, we employ the SSFA model proposed by Fusco and Vidoli (2013) that allows us to get hospital efficiency scores robust to the presence of spatial dependence and, then, to robustly infer the significant presence of spatial dependence in the technical efficiency of hospitals. Overall, our findings suggest an insignificant role for spatial dependence in the efficiency of Italian hospitals, irrespective of the functional form of the production function (i.e. Cobb-Douglas and Translog) and of the specific form of spatial dependence implicit in the weights matrix (i.e. spatial contiguity, institutional contiguity). Therefore, we conclude that it does not seem to be a significant presence of spatial dependence in the efficiency behaviour of hospitals, consistently with the economic theory (Longo et al., 2017).

Comparing our results with the previous evidence on this issue, they are in line with those provided by Longo et al. (2017) for hospitals in the UK. However, our findings are in contrast to the evidence in Herwartz and Strumann (2012) that, employing a two-stage approach, find a significant negative spatial interdependence among German hospitals, presumably due to the competition induced by the introduction of a DRG-based prospective reimbursement system. Since in the Italian NHS, as well as in the UK, the main hospital reimbursement mechanism, though with a few differences, is also a DRG-based prospective system, such difference in the results would not seem to depend strongly on the different institutional contexts, but rather is supposed to depend on the robustness of the empirical approach to incorporate spatial dependence in the efficiency analysis. Under this perspective, the methodological approach employed in this paper provides a more consistent way to estimate the efficiency of hospitals in presence of spatial dependence and, in turn, to test its significant role in affecting the efficiency behaviour of hospitals. Indeed, apart from offering a more accurate description of hospitals' behaviour, the robust estimation of the presence of spatial dependence in hospital efficiency has also important policy implications in terms of the effects of competition and merging policies in the healthcare market (e.g., Brekke et al., 2016; Longo et al., 2017), underlining the importance of the proposed robust approach.

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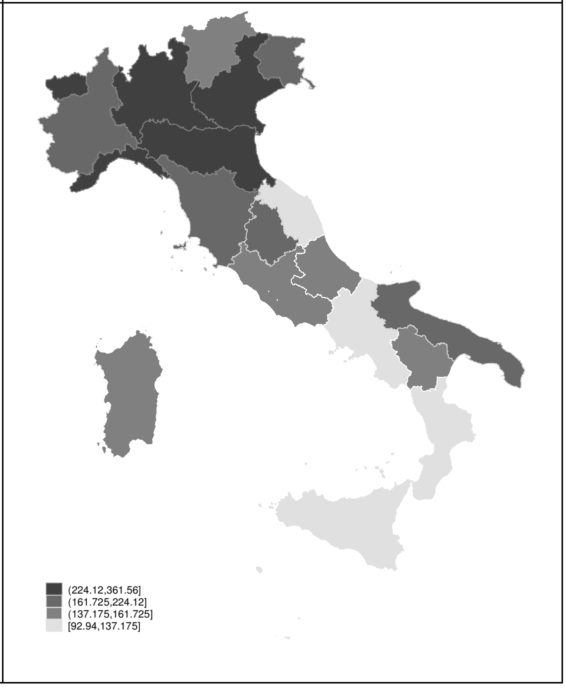
Tables and Graphs

Graph 1. Geographical distribution of Italian hospitals by average number of beds (year 2010)

<table>
<tr><td>Average number of beds per hospital (only public)</td><td>Average number of beds per hospital (public and accredited private)</td></tr>
<tr><td>

</td><td>



</td></tr>
</table>

Source: our elaboration on data provided by the Italian Department of Healthcare (Ministero della Salute, 2013) .

Graph 2. Geographical distribution of Italian hospitals by average number of discharged acute patients and case-mix index (year 2010)

Average number of discharged acute patients per hospital (public and accredited private)	Average case-mix index (public and accredited private)
	

Source: our elaboration on data provided by the Italian Department of Healthcare (Ministero della Salute, 2012).

Table 1. Sample composition by geographical area – year 2010

Geographical area	***Hospitals***		***Discharges***		***Average discharges (acute patients)***
	N. obs.	***%***	***Discharges (number of acute patients)***	***%***	
North	255	*29.45*	3,025,431.79	*43.55*	11,864.44
Centre	188	*21.71*	1,414,961.64	*20.37*	7,526.39
South and islands	423	*48.85*	2,506,288.18	*36.08*	5,925.03
All sample	**866**	***100.00***	**6,946,681.61**	***100.00***	**8,021.57**

Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 2. Sample statistics of virtual revenue composition by geographical area – year 2010

Geographical area	***N. obs.***	***Average estimated revenue***	***S.D.***
North	255	48,687,322.24	52,317,365.70
Centre	188	30,046,264.46	44,645,848.96
South and islands	423	21,010,405.28	28,206,740.75
All sample	**866**	**31,121,670.12**	**41,999,995.80**

Source: our elaboration on data provided by the Italian Department of Healthcare.
Notes: virtual revenue estimated using the national DRG system (*Decreto del Ministero della Salute del 18 dicembre 2008*) and the tariffs system agreement for interregional mobility (TUC 2012) for all discharged acute patients at hospital level (in euro).

Table 3. Descriptive Statistics of the employed variables

Variables	Meaning	Descriptive Statistics		
		Obs.	*Mean*	*S.D.*
DRG_W_REVENUE	Revenue weighted by TUC tariff for basic one point DRG (2,490 euro)	866	12,498.76	16,866.53
BEDS	Number of beds, at hospital level	866	205.20	248.15
PHYSICIANS	Number of full time equivalent physicians, at hospital level	866	135.34	171.95
NURSES	Number of full time equivalent nurses, at hospital level	866	287.10	404.46
O_PERS	Number of full time equivalent other personnel, at hospital level	866	247.65	379.65

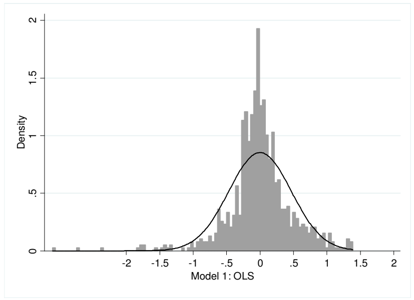
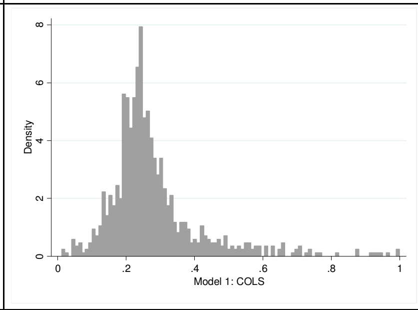
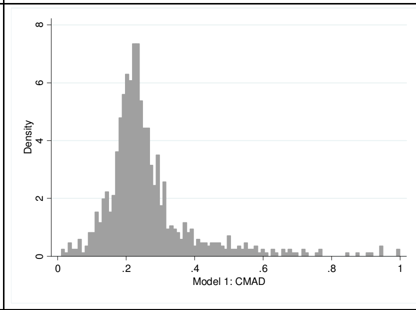
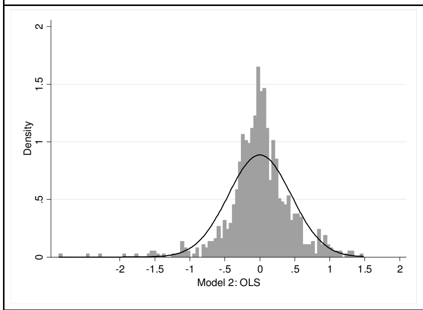
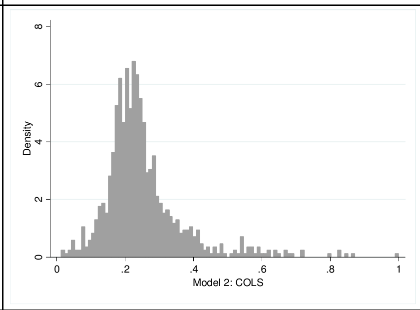
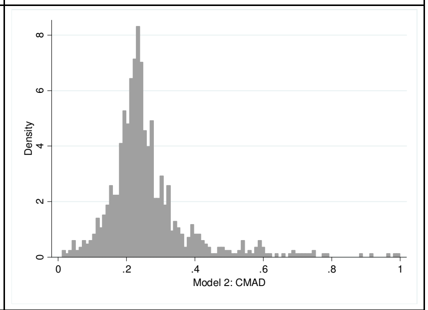
Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 4. OLS estimates

VARIABLES	*Dependent variable* DRG_W_REVENUE (log)	
	(1)	(2)
Constant	3.7260***	3.8399***
	(0.0789)	(0.1726)
BEDS (log)	0.4902***	0.4877***
	(0.0383)	(0.0381)
PHYSICIANS (log)	0.2855***	0.2694***
	(0.0314)	(0.0321)
NURSES (log)	0.1807***	0.1845***
	(0.0315)	(0.0318)
O_PERS (log)	0.1142***	0.1227***
	(0.0373)	(0.0397)
Observations	866	866
Regional dummies	no	yes
F (p-value)	0.0000	0.0000
AIC	1151.105	1119.719
R-squared	0.8611	0.8712
Adj R-squared	0.8605	0.8679
F-test [(a)] (p-value)	-	3.76*** (0.000)

Source: our elaboration on data provided by the Italian Department of Healthcare.
*** p<0.01, ** p<0.05, * p<0.1.
(a) F-test = F-test for joint significance of regional fixed effects.

Graph 3. Histograms of OLS residuals, COLS and CMAD efficiency estimates - Cobb-Douglas production function

Mod (1)					
OLS residuals		COLS		CMAD	
					
Skewness	-0.7818	Obs.	866	Obs.	866
Skewness test (p-value)	0.0000	Mean efficiency	0.2778	Mean efficiency	0.2613
M3T test - Coelli (1995)	-9.3929***	St. dev.	0.1368	St. dev.	0.1323
Mod (2)					
OLS residuals		COLS		CMAD	
					
Skewness	-0.8050	Obs.	866	Obs.	866
Skewness test (p-value)	0.0000	Mean efficiency	0.2511	Mean efficiency	0.2605
M3T test - Coelli (1995)	-9.6655***	St. dev.	0.1169	St. dev.	0.1239

Source: our elaboration on data provided by the Italian Department of Healthcare.
*** p<0.01, ** p<0.05, * p<0.1.

Table 5. SFA estimates – Cobb-Douglas and Translog production functions (u_i *half normal*)

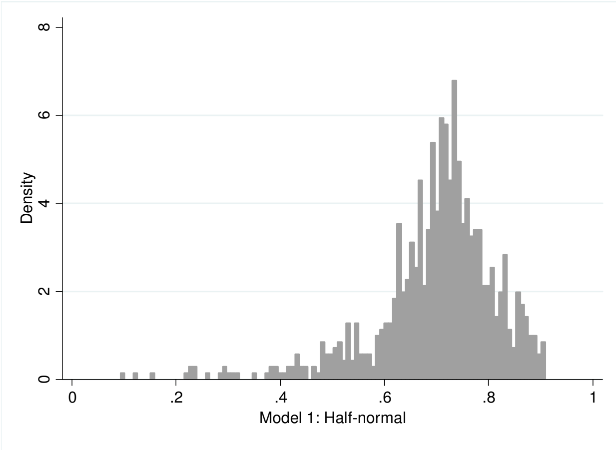
VARIABLES	*Dependent variable* DRG_W_REVENUE (log)			
	(1)	(2)	(3)	(4)
Constant	4.2643***	4.3154***	3.8244***	4.0048***
	(0.0959)	(0.1713)	(0.2853)	(0.3145)
BEDS (log)	0.4939***	0.4820***	0.8072***	0.6848***
	(0.0378)	(0.0370)	(0.1996)	(0.1957)
PHYSICIANS (log)	0.2389***	0.2148***	0.5360***	0.5505***
	(0.0305)	(0.0300)	(0.1490)	(0.1459)
NURSES (log)	0.1695***	0.1740***	0.0157	0.1117
	(0.0311)	(0.0310)	(0.1517)	(0.1502)
O_PERS (log)	0.1345***	0.1538***	-0.1111	-0.1247
	(0.0363)	(0.0380)	(0.1693)	(0.1693)
BEDS_SQR (log)	-	-	-0.2557***	-0.2018**
	-	-	(0.0924)	(0.0908)
PHYSICIANS_SQR (log)	-	-	0.2644***	0.2216***
	-	-	(0.0579)	(0.0572)
NURSES_SQR (log)	-	-	-0.2101***	-0.2701***
	-	-	(0.0696)	(0.0688)
O_PERS_SQR (log)	-	-	0.1487	0.1385
	-	-	(0.0998)	(0.0989)
BEDS_PHYSICIANS (log)	-	-	-0.6703***	-0.6469***
	-	-	(0.1232)	(0.1206)
BEDS_NURSES (log)	-	-	0.6855***	0.6331***
	-	-	(0.1473)	(0.1480)
BEDS_O_PERS (log)	-	-	0.2783*	0.2607*
	-	-	(0.1437)	(0.1410)
PHYSICIANS_NURSES (log)	-	-	0.2060	0.2595**
	-	-	(0.1338)	(0.1313)
PHYSICIANS_O_PERS (log)	-	-	-0.0843	-0.1035
	-	-	(0.1400)	(0.1367)
NURSES_O_PERS (log)	-	-	-0.4046***	-0.3292***
	-	-	(0.1155)	(0.1137)
Observations	866	866	866	866
Regional dummies	No	yes	no	yes
σ_u^2	0.2595*** (0.0396)	0.2730*** (0.0366)	0.2248*** (0.0344)	0.2317*** (0.0324)
σ_v^2	0.1207*** (0.0129)	0.0992*** (0.0112)	0.1118*** (0.0113)	0.0960*** (0.0102)
σ^2	0.3816	0.3722	0.3365	0.3277
γ	0.6825	0.7334	0.6679	0.7071
LR test	32.0882***	40.8907***	32.4449***	38.7179***
AIC	1123.017	1083.044	1052.426	1022.522
Mean efficiency	0.7002	0.6956	0.7164	0.7139

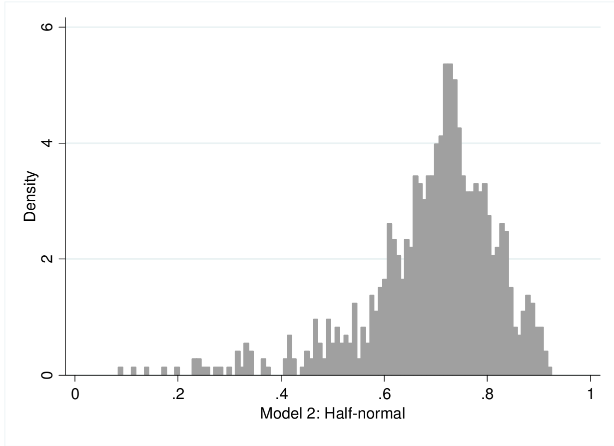
Source: our elaboration on data provided by the Italian Department of Healthcare.

*** p<0.01, ** p<0.05, * p<0.1, , standard errors in parentheses.

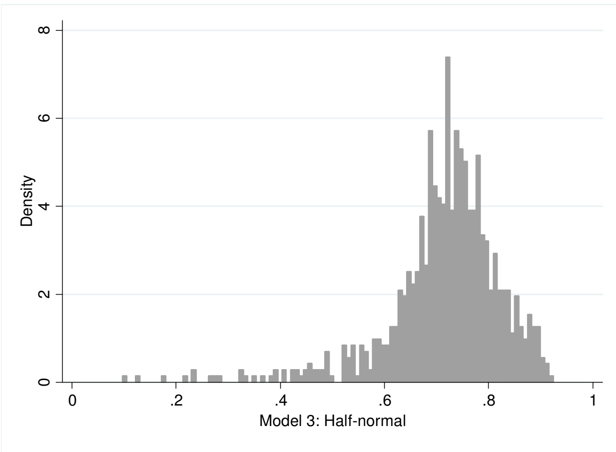
Graph 4. Histograms, pairwise correlation and geographical distribution of efficiency estimates

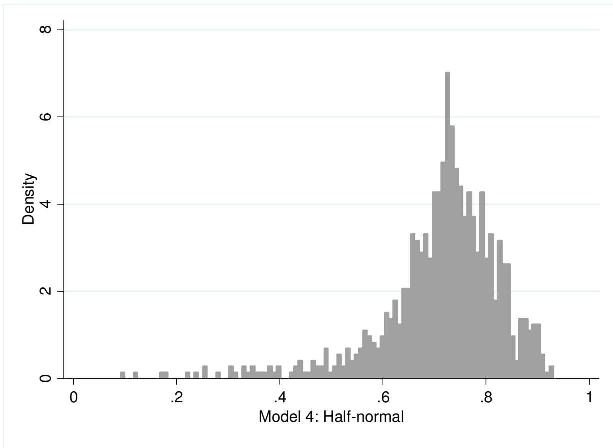
Cobb-Douglas production functions





Translog production functions





Pairwise correlation matrix

1.0000			
0.9548	1.0000		
0.9480	0.9077	1.0000	
0.9123	0.9519	0.9604	1.0000

Average efficiency scores distribution

Geographical area	***N. obs.***	(1)	(2)	(3)	(4)
North	255	0.7069 (0.1016)	0.7020 (0.1117)	0.7172 (0.0998)	0.7190 (0.1062)
Centre	188	0.7098 (0.0991)	0.6971 (0.1124)	0.7213 (0.0914)	0.7165 (0.0999)
South and islands	423	0.6919 (0.1314)	0.6910 (0.1402)	0.7137 (0.1222)	0.7097 (0.1287)
All sample	***866***	**0.7002 (0.1168)**	**0.6956 (0.1265)**	**0.7164 (0.1096)**	**0.7139 (0.1165)**

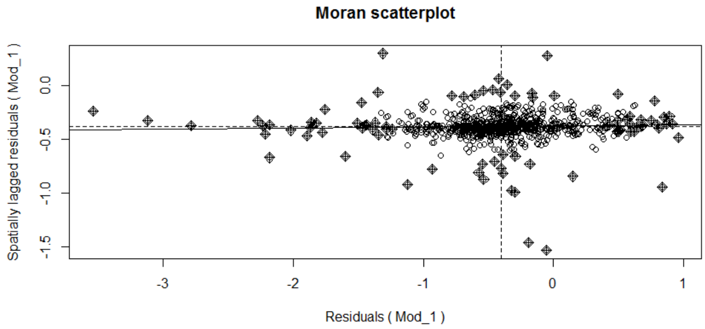
Source: our elaboration on data provided by the Italian Department of Healthcare.
Note: standard deviations in parentheses.

Graph 5. Spatial autocorrelation of the SFA residuals based on the Euclidean distance

Model 1

Moran I test under randomisation
data: residuals(Mod_1)
weights: Mod_1$list_w
Moran I statistic standard deviate = 0.91518, p-value = 0.18
alternative hypothesis: greater
sample estimates:

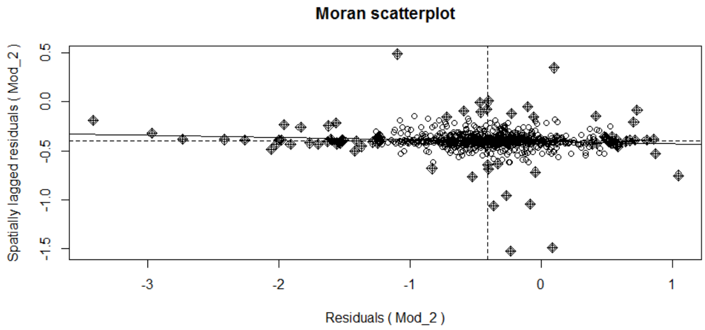
Moran I statistic	Expectation	Variance
0.0084623361	-0.0011560694	0.0001104581



Model 2

Moran I test under randomisation
data: residuals(Mod_2)
weights: Mod_2$list_w
Moran I statistic standard deviate = -1.9687, p-value = 0.9755
alternative hypothesis: greater
sample estimates:

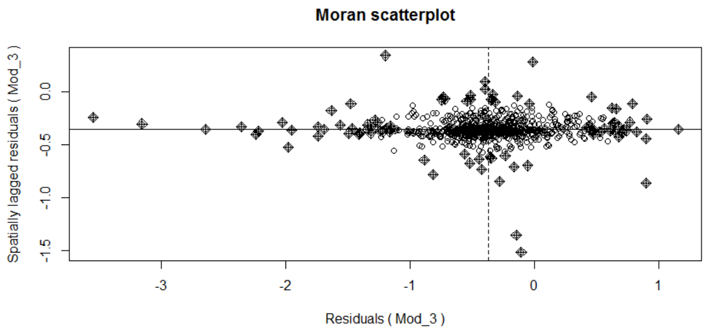
Moran I statistic	Expectation	Variance
-0.0218467366	-0.0011560694	0.0001104549



Model 3

Moran I test under randomisation
data: residuals(Mod_3)
weights: Mod_3$list_w
Moran I statistic standard deviate = 0.15903, p-value = 0.4368
alternative hypothesis: greater
sample estimates:

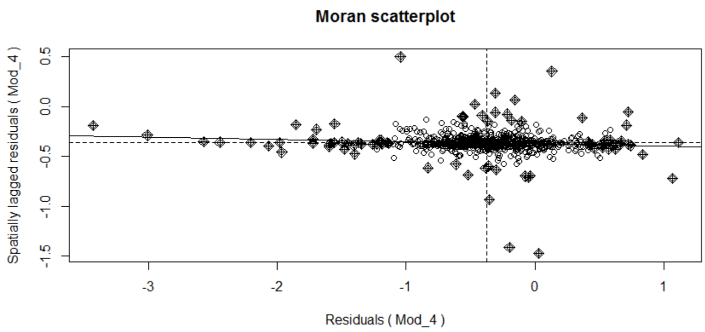
Moran I statistic	Expectation	Variance
0.0005139307	-0.0011560694	0.0001102742



Model 4

Moran I test under randomisation
data: residuals(Mod_4)
weights: Mod_4$list_w
Moran I statistic standard deviate = -2.0811, p-value = 0.9813
alternative hypothesis: greater
sample estimates:

Moran I statistic	Expectation	Variance
-0.0230111511	-0.0011560694	0.0001102815



Source: our elaboration on data provided by the Italian Department of Healthcare.

Table 6. SSFA and SEM estimates using a spatial contiguity matrix based on the Euclidean distance

VARIABLES	SSFA				SEM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	4.3551***	4.1702***	3.8536***	3.9092***	3.7296***	4.3830***	3.3994***	3.2557***
	(0.1251)	(0.1754)	(0.2890)	(0.3218)	(0.3247)	0.4453	(0.4037)	(0.4811)
BEDS (log)	0.4933***	0.4913***	0.7915***	0.7123***	0.4988***	0.4825***	0.6742***	0.5152**
	(0.0378)	(0.0370)	(0.2019)	(0.1955)	(0.0379)	0.0370	(0.2085)	(0.2055)
PHYSICIANS (log)	0.2371***	0.2159***	0.5410***	0.5249***	0.2409***	0.2148***	0.4799***	0.2936*
	(0.0305)	(0.0300)	(0.1495)	(0.1467)	(0.0304)	0.0300	(0.1131)	(0.1628)
NURSES (log)	0.1688***	0.1697***	0.0178	0.1234	0.1705***	0.1738***	0.2727	0.3443**
	(0.0314)	(0.0303)	(0.1504)	(0.1491)	(0.0311)	0.0310	(0.1653)	(0.1671)
O_PERS (log)	0.1353***	0.1547***	-0.1022	-0.1577	0.1236***	0.1536***	-0.2255	0.1571
	(0.0366)	(0.0379)	(0.1708)	(0.1688)	(0.0368)	0.0380	(0.1464)	(0.1891)
BEDS_SQR (log)	-	-	-0.2523***	-0.1965**	-	-	-0.1245*	-0.0490
	-	-	(0.0925)	(0.0902)	-	-	(0.0687)	(0.1251)
PHYSICIANS_SQR (log)	-	-	0.2606***	0.2319***	-	-	0.0525	0.2276***
	-	-	(0.0584)	(0.0574)	-	-	(0.0342)	(0.0581)
NURSES_SQR (log)	-	-	-0.2128***	-0.2658***	-	-	-0.1903***	-0.1812**
	-	-	(0.0699)	(0.0677)	-	-	(0.0411)	(0.0799)
O_PERS_SQR (log)	-	-	0.1500	0.1313	-	-	0.3164	0.1249
	-	-	(0.1000)	(0.0983)	-	-	(0.2047)	(0.0935)
BEDS_PHYSICIANS (log)	-	-	-0.6673***	-0.6591***	-	-	-0.5565***	-0.4748***
	-	-	(0.1232)	(0.1202)	-	-	(0.1671)	(0.1661)
BEDS_NURSES (log)	-	-	0.6887***	0.6087***	-	-	0.5777***	0.3579**
	-	-	(0.1471)	(0.1468)	-	-	(0.1242)	(0.1658)
BEDS_O_PERS (log)	-	-	0.2734*	0.2741*	-	-	0.0894	0.1585
	-	-	(0.1438)	(0.1405)	-	-	(0.0921)	(0.1673)
PHYSICIANS_NURSES (log)	-	-	0.2071	0.2602**	-	-	0.3256*	0.2094
	-	-	(0.1338)	(0.1314)	-	-	(0.1574)	(0.1594)
PHYSICIANS_O_PERS (log)	-	-	-0.0851	-0.0966	-	-	0.0275	-0.1184
	-	-	(0.1403)	(0.1356)	-	-	(0.0761)	(0.1373)
NURSES_O_PERS (log)	-	-	-0.4047***	-0.3201***	-	-	-0.5696***	-0.3027**
	-	-	(0.1155)	(0.1127)	-	-	(0.1947)	(0.1212)
Observations	866	866	866	866	866	866	866	866
Regional dummies	no	yes	No	yes	no	yes	no	yes
σ_u^2	-	-	-	-	0.1180*** (0.0003)	0.0994*** (0.0146)	0.0362*** (0.0057)	0.0953 0.0139
σ_{dmu}^2	0.2643*** (0.0396)	0.2614*** (0.0365)	0.2266*** (0.0345)	0.2216*** (0.0321)	-	-	-	-
σ_v^2	0.1187*** (0.0128)	0.1015*** (0.0113)	0.1111*** (0.0114)	0.0975*** (0.0103)	0.2665*** (0.0015)	0.2730*** (0.0243)	0.5527*** (0.0223)	0.2801 0.0238
σ^2	0.3830	0.3635	0.3378	0.3198	0.3846	0.3724	0.5890	0.3754
γ	0.6901	0.7204	0.6710	0.6944	0.3069	0.2669	0.0615	0.2538
ρ	0.1669	-0.3365	0.0685	-0.4108	0.0634	-0.0043	0.1032	-0.0479
LR test	33.963***	46.692***	32.703***	46.111***	-	-	-	-
AIC	1139.142	1131.298	1090.168	1088.744	1122.386	1085.084	1168.498	1055.312

Source: our elaboration on data provided by the Italian Department of Healthcare.
*** p<0.01, ** p<0.05, * p<0.1, standard errors in parentheses.

Table 7. Robustness checks on SSFA estimates using a spatial contiguity matrix at LHA level

VARIABLES	SSFA			
	(1)	(2)	(3)	(4)
Constant	4.4683***	4.2778***	3.9578***	3.8991***
	(0.1278)	(0.1544)	(0.2919)	(0.3017)
BEDS (log)	0.4858***	0.4865***	0.7489***	0.6928***
	(0.0378)	(0.0367)	(0.1992)	(0.1936)
PHYSICIANS (log)	0.2196***	0.2241***	0.5541***	0.5264***
	(0.0311)	(0.0300)	(0.1476)	(0.1471)
NURSES (log)	0.1717***	0.1739***	0.0830	0.0715
	(0.0316)	(0.0304)	(0.1534)	(0.1497)
O_PERS (log)	0.1469***	0.1474***	-0.1402	-0.0809
	(0.0374)	(0.0377)	(0.1684)	(0.1710)
BEDS_SQR (log)	-	-	-0.2425***	-0.1931**
	-	-	(0.0917)	(0.0905)
PHYSICIANS_SQR (log)	-	-	0.2425***	0.2318***
	-	-	(0.0582)	(0.0569)
NURSES_SQR (log)	-	-	-0.2320***	-0.2640***
	-	-	(0.0700)	(0.0683)
O_PERS_SQR (log)	-	-	0.1333	0.1441
	-	-	(0.0999)	(0.0980)
BEDS_PHYSICIANS (log)	-	-	-0.6674***	-0.6392***
	-	-	(0.1222)	(0.1201)
BEDS_NURSES (log)	-	-	0.6694***	0.6185***
	-	-	(0.1474)	(0.1472)
BEDS_O_PERS (log)	-	-	0.2957**	0.2446*
	-	-	(0.1422)	(0.1414)
PHYSICIANS_NURSES (log)	-	-	0.2238*	0.2774**
	-	-	(0.1333)	(0.1304)
PHYSICIANS_O_PERS (log)	-	-	-0.0732	-0.1294
	-	-	(0.1387)	(0.1366)
NURSES_O_PERS (log)	-	-	-0.3834***	-0.3240***
	-	-	(0.1162)	(0.1123)
Observations	866	866	866	866
Regional dummies	No	yes	no	yes
σ_{dmu}^2	0.2755*** (0.0398)	0.2614*** (0.0365)	0.2338*** (0.0345)	0.2215*** (0.0321)
σ_v^2	0.1127*** (0.0126)	0.1017*** (0.0114)	0.1073*** 0.0112	0.0979*** (0.0103)
σ^2	0.3887	0.3634	0.3413	0.3198
γ	0.7096	0.7200	0.6854	0.6935
ρ	0.2551	-0.2081	0.2124	-0.2407
LR test	43.378	46.102***	39.403***	44.654***
AIC	1129.728	1131.889	1083.468	1090.202

Source: our elaboration on data provided by the Italian Department of Healthcare.
*** p<0.01, ** p<0.05, * p<0.1, standard errors in parentheses.

Table 8. Robustness checks of SSFA estimates using a spatial contiguity matrix at provincial level

VARIABLES	SSFA			
	(1)	(2)	(3)	(4)
Constant	4.4872***	4.2663***	3.9823***	3.9125***
	(0.1323)	(0.1398)	(0.2907)	(0.2979)
BEDS (log)	0.4887***	0.4850***	0.7422***	0.6946***
	(0.0376)	(0.0366)	(0.1985)	(0.1934)
PHYSICIANS (log)	0.2214***	0.2221***	0.5421***	0.5468***
	(0.0310)	(0.0297)	(0.1462)	(0.1464)
NURSES (log)	0.1704***	0.1759***	0.0943	0.0640
	(0.0315)	(0.0303)	(0.1530)	(0.1494)
O_PERS (log)	0.1457***	0.1476***	-0.1305	-0.1006
	(0.0372)	(0.0378)	(0.1678)	(0.1691)
BEDS_SQR (log)	-	-	-0.2480***	-0.1803**
	-	-	(0.0920)	(0.0909)
PHYSICIANS_SQR (log)	-	-	0.2447***	0.2254***
	-	-	(0.0578)	(0.0567)
NURSES_SQR (log)	-	-	-0.2369***	-0.2642***
	-	-	(0.0701)	(0.0680)
O_PERS_SQR (log)	-	-	0.1282	0.1461
	-	-	(0.0995)	(0.0985)
BEDS_PHYSICIANS (log)	-	-	-0.6550***	-0.6605***
	-	-	(0.1211)	(0.1202)
BEDS_NURSES (log)	-	-	0.6576***	0.6270***
	-	-	(0.1478)	(0.1472)
BEDS_O_PERS (log)	-	-	0.3111**	0.2287
	-	-	(0.1410)	(0.1414)
PHYSICIANS_NURSES (log)	-	-	0.2233	0.2725**
	-	-	(0.1331)	(0.1295)
PHYSICIANS_O_PERS (log)	-	-	-0.0914	-0.1053
	-	-	(0.1375)	(0.1357)
NURSES_O_PERS (log)	-	-	-0.3767***	-0.3231***
	-	-	(0.1162)	(0.1120)
Observations	866	866	866	866
Regional dummies	No	yes	no	yes
σ_{dmu}^2	0.2755*** (0.0396)	0.2585*** (0.0364)	0.2331 0.0342	0.2223*** (0.0322)
σ_v^2	0.1124*** (0.0125)	0.1019*** (0.0114)	0.1070 0.0111	0.0973*** (0.0103)
σ^2	0.3884	0.3609	0.3404	0.3200
γ	0.7102	0.7172	0.6854	0.6956
ρ	0.2917	-0.2947	0.2702	-0.3117
LR test	44.745***	48.887***	42.021***	46.266***
AIC	1128.360	1129.103	1080.850	1088.589

Source: our elaboration on data provided by the Italian Department of Healthcare.
*** p<0.01, ** p<0.05, * p<0.1, standard errors in parentheses.